

**THREE ESSAYS ON COMPETITIVE STRATEGIES
FOR DIGITAL PLATFORM BUSINESSES**

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Submitted to the Graduate Faculty of
Katz Graduate School of Business in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy

University of Pittsburgh

2018

UNIVERSITY OF PITTSBURGH
KATZ GRADUATE SCHOOL OF BUSINESS

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As businesses in many industries adopt the platform business model, many aspects of the traditional business are going through a shake-up, including competition and strategies for gaining competitive advantage. When platforms are competing with each other, the network effects due to having a strong installed base create a strategic advantage and shape the competition. Additionally, another level of competition in the world of platforms is between complementors on a given platform which is also influenced by the presence of the network effects. In the three studies of this dissertation, we focus on competitive strategies for digital platform businesses. In the first essay, we look at competition between platforms and examine the emergence of Winners-Take-Some (WTS) market outcome in IT platform markets, where such markets are expected to yield a Winner-Takes-All (WTA) outcome. We use the cyclical video game console market as an appropriate context to investigate the influential factors in the market outcome in platform markets. We find a consistent increase in multi-homing among the most popular video-games that can pave the way for the emergence of WTS outcome. In the second essay, we are turning our focus to the strategies that platforms can adopt to improve emerging success metrics such as user engagement. We examine how digital content platforms can improve users' engagement by providing popularity information signals. We evaluate the effect of conflicting and aligned information signals on users' engagement in the context of music content platforms. We find that conflicting popularity information signals are more effective in increasing user engagement than the aligned popularity information signals. In the third essay and in the context of mobile app platforms, we

focus on the competition between complementors. We study the role of app category characteristics on the performance of mobile app developers who offer apps in those categories and strive to gain competitive advantage. We evaluate category concentration and category popularity as two important factors and find that respectively, they negatively and positively influence new app's performance for a given developer. We find that the negative effect of category concentration is stronger than the positive effect of category popularity.

Keywords: digital platforms, competitive strategies, network effects, winners-take-some, user engagement, app category characteristics

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PREFACE

DEDICATION

To my most loving and caring Maman and Baba, Masi and Sadegh: the two pillars of my being

To my brilliant and compassionate husband, Arash: the light of my world

And to my kind and supportive brother, Ehsan.

ACKNOWLEDGEMENTS

Every journey starts with perceptions and expectations of what lies ahead. Starting the PhD program at Katz was no exception. I entered the program, knowing that I'd be putting down long hours of hard work to complete the course work and conduct high quality research. In the last five years though, I learnt that completing a PhD program is about more than just hard work. It's about resilience, perseverance, and grit. It takes standing up after falling down and iteration, seeking help from anyone and everyone, and just not giving up... Going through this journey and finishing the marathon would have not been possible for me if it was not for all the support, mentoring, and love that I have received from an army of people.

I extend my gratitude to my advisor, Dr. Chris Kemerer, for having faith in me and always reminding me to look at the big picture and not to lose sight of the big prize. I am thankful for all the support that I received and all the things that I learned from him. His mentorship has helped me think big and grow as an independent researcher. I also want to thank my dissertation committee members: Dr. Narayan Ramasubbu, Dr. Charles Liu and Dr. Dennis Galletta. I am thankful to Dr. Narayan Ramasubbu, for devoting his time and attention to help me find my path, make progress and manage my academic life. I thank him for reminding me that I should think of my personal welfare when making big decisions in life. I am thankful to Dr. Charles Liu, for all the long phone calls and Skype meetings and brainstorming sessions to work on interesting and challenging research problems. I thank him for greatly helping me with data collection for the third essay. Last but not least, I am thankful to Dr. Dennis Galletta, for his continued support and having his door always open for any question and concern that I needed to discuss.

During my doctoral studies, I had the chance to interact with, learn and receive support from many other individuals. I am thankful to late Dr. Kevin Kim for teaching me the fundamentals of statistics. I am grateful to Dr. Sherae Daniel for getting me involved in research projects from my early days in the PhD program. I am grateful to Seth Miller, Jeremy Packer and Akhil Tolani at Rapchat for their tremendous help with the data collection for my second essay. I am thankful to Vahid Torkaman for his generous help with the data collection for my third essay. I extend my deepest gratitude to Carrie Woods and Chris Gurskey at the doctoral office. Carrie has always been a phenomenal source of care and support with any and all kinds of problems I have faced during my time at Katz. I am grateful to my classmates Shivendu Singh, Dimitar Kunev, Dr. Qin Weng, Dr. David Eargle, and Dr. Brian Dunn. They have been a great help and moral support during all the ups and downs we have shared during the PhD studies. I am deeply indebted to their camaraderie.

I am forever thankful to Arash, my love, my husband. Navigating this journey and crossing the finish line would have not been possible without having him by my side. Day in and day out, the PhD life has brought about challenges to face and problems to solve. With his beautiful soul, generous heart and smart mind, Arash doesn't rest until he finds a way to help me out, and he always comes through. And in the times of accomplishments, he made sure I enjoyed the moment, and he celebrated me and my achievements. Though we spent most of our doctoral studies 321 miles away from each other, his lovely and reliable presence in my life and in my heart empowered me to keep up the fight. Thank you Azizam!

To my parents, Maman, Baba, thank you. Thank you for believing in me, thank you for your unconditional love, never-ending support and devotion. Masi and Sadegh are the reasons I am who I am and have achieved what I achieved. During my studies, my day would start with an inter-continental phone call and would end with another one. Talking to them has been my routine to get energized and to unwind every day of my PhD life. I am immeasurably grateful for their compassion, wise advice and continued support.

To my brother, Ehsan, thank you. I am thankful for his faith in me, for encouraging me and for always having my back. His kind and supportive presence in my life has blessed me with peace of mind and I am forever thankful for that. I also want to thank Pegah (my sister-in-law); Gohar and Bahman (my parents-in-law); Reza and Shabnam (my brother- and sister-in-law). Their love, support, and confidence in me have been an invaluable source of encouragement during my studies.

During my PhD life, the sad moments of misery and despair would not last too long because I am blessed with the most amazing friends. Near or far, they have boosted my morale and encouraged me to do my best, try harder and not to give up. I am thankful to my BFFs, Nasim Eftekhari in LA and Sepideh Farjami in Milan. I am grateful for my wonderful friends in Pittsburgh: Azarin Zarassi, Laleh Gharanjik, Matineh Eybpoosh, Atousa Mashayekhi, Maryam Shabani, Ali Pakzad, Fattane Jabbari, Amin Tajgardoona, Majid Darvishan, Zahra Rahimi, Sareh Yousefzade, Mostafa Mirshekari, Salim Malakouti, and Hanieh Ghasemi. I thank them for patiently listening to my rants, being my consultants, and cheering me up with a cup of tea, a drink or a trip to Page Dairy Mart.

1.0 INTRODUCTION

In recent years, the platform revolution has transformed the business world. Platforms enable interactions between two (or more) sides of a market, mainly complementors and consumers, and they rely on facilitating the exchanges between the multiple sides of the market to create value. As businesses in many industries adopt the platform business model, many aspects of traditional business are going through a shake-up, including competition and strategies for gaining competitive advantage.

The change in the nature of the competition in the world of platforms is partly due to the presence of network effects. With the positive indirect or cross-side network effects, the value created for participants on one side of the platform increases as there are more participants on the other side of the platform. On the other hand, competition effect due to an overcrowded presence of complementors can create a glut of complementors and heightened competition. In that case, the increase in number of strong incumbents on one side can result in decreased value for all the participants on the same side.

At the platform level and when platforms are competing with each other, network effects due to having a strong installed base can create a strategic advantage and shape the competition (Katz and Shapiro 1985; Rochet and Tirole 2003). However, there are factors that can attenuate network effects and consequently alter the course of competition between platforms, such as prevalence of multi-homing (Armstrong 2006; Doganoglu and Wright 2006). In the first essay of this dissertation, we study the competition among platforms and investigate how the prevalence of multi-homing affects market outcomes.

In the first essay and in chapter two, we look at competition between platforms and examine the emergence of a Winners-Take-Some (WTS) market outcome in IT platform markets. In such markets, market outcome expectation based on both academic research and marketplace has been a Winner-Takes-All (WTA) outcome, i.e. a single dominant market leader with more than 50% of the market share (Eisenmann et al. 2006; Gawer and Cusumano 2002; Katz and Shapiro 1985; Shapiro and Varian 1999).

But in recent years, a disruption in this trend has been observed in some networked markets, where no single platform holds a dominant share, resulting in a WTS outcome (Bresnahan et al. 2015; Liu et al. 2012). For platform owners, whether a WTA or WTS outcome is expected in a market competition, the strategic decisions they make and the competitive strategies they adopt are likely to be different. With a WTA outcome, more up-front subsidization for winning early market share is advised. But with a WTS outcome, platform owners need to have less up-front subsidization and fight *in* the market rather than *for* the market (Kemerer et al. 2013).

We use the cyclical video game console market as an appropriate context to investigate influential factors in the market outcome that can bring about a WTS. Evaluating these factors, prior works suggest the importance of multi-homing in weakening the network effects in platform markets which can pave the way for a WTS outcome (Bresnahan et al. 2015; Corts and Lederman 2009; Rochet and Tirole 2003) . Building on prior studies and using three sets of data, we empirically test the hypothesis that an increase in multi-homing of the most-popular complements has shaped the market in this competition to yield a WTS outcome. We find that 65% of the most-popular games in the Internet Class are multi-homing, a distinct increase from prior competitions. We argue that this increase is likely due to changes in the cost structure of software game development, as well as the increasingly downloadable nature of the games.

In the world of platforms, the platform businesses compete with each other by adopting strategies that encourage more participation on both sides of the market and allow for more value creation. This is important due to the presence of network effects: as participation and activity on one side of the platform increases, the gain and value for participants on the other side of the platform increases (Farrell and Klemperer 2007). One such strategy is to enhance the design of the platform to better equip users with their required information with the goal of improving their engagement with the platform. In the second essay of this dissertation, we study the design of platforms and how informational signals can increase the users' engagement on the platform.

In the second essay and in chapter three, we are turning our focus to the strategies platforms adopt to gain competitive advantage, and in particular the strategy of enhancing the design of the platforms. The platform markets literature suggests that for content platforms (i.e. platforms enabling the exchange of content), user engagement is an emerging success metric and that improving user engagement can help platforms gain a competitive advantage. To invoke such desired user behavior, research literature suggests that platforms can take an active role and disseminate information signals (e.g. in the form of ratings, reviews, etc.) to the users (Aral et al. 2013; Godes et al. 2005).

In this study, we examine how information signals accompanying content can influence user engagement in content platforms. These information signals can be aligned with each other or in conflict with each other, thereby influencing user engagement differently. To better understand these effects, we draw from the information foraging theory and social foraging model that explain a user's behavior in an information search environment similar to a content platform (Pirolli 2009; Pirolli and Card 1999). In these environments, heterogeneity of information signals

can reduce the redundancy of received information by a user, increase their discovery of content on the platform and result in more user engagement.

We hypothesize that in content platforms, since conflicting signals are more heterogeneous than aligned signals, they are more effective in increasing user engagement than aligned signals. We test our hypothesis in a randomized field experiment in the context of music content platform, using popularity of songs as information signals. The results of this field experiment show when users are exposed to conflicting signals, they are more engaged with the platform than when they are exposed to no information signal or aligned information signals.

Due to the presence of network effects on platforms, the locus of value creation changes from inside the firm to outside the firm, and consequently the focus of organizational attention shifts from inside to outside. As a result, platform companies redefine organizational boundaries by building external ecosystems where value is created (Parker et al. 2016). In an ecosystem, participation of partners (or complementors) creates value for both the platform and the partners. In such ecosystems, another level of competition surfaces between complementors on a given platform as they compete to improve their performance and gain a competitive advantage over other complementors. In the third essay of this dissertation and in the context of mobile app platforms, we study the role of app category characteristics in how complementors can improve the performance of their products.

The third piece of this dissertation in chapter four focuses on the competitive strategies that complementors adopt in order to succeed on a platform. The context of this study is mobile app platforms, where mobile app developers (as complementors) adopt a myriad of strategies to improve their performance. One such strategy is diversification of app offerings across different app categories. In adopting this strategy, the choice of for which app categories to develop is not

a trivial decision, as it may have consequences for how well the app will be adopted and downloaded by the users. The success of the newly released apps is in part dependent on the characteristics of the app categories they are offered in. Prior works in other industries have examined how features of product markets can improve or impede the performance of firms and their newly introduced products. These characteristics include competition within a product-market and the popularity of product-market based on the demand for it (Boudreau 2010; Cennamo and Santalo 2010; Markovich and Moenius 2009; Simonsohn 2010). Since the mobile app platform is a networked market, these two forces can significantly influence the performance of a newly released app. The category concentration increases as the competition becomes more intense and more strong incumbents are present in a mobile app category, leading to a glut of developers (Boudreau 2012). Category popularity increases as there is more demand for the apps in a category, triggering an indirect positive network effect (Venkatraman and Lee 2004). Given the tension between these two opposing forces, Venkatraman and Lee raise the need for further investigation into these two effects, and their trade-off.

We hypothesize that two opposing category characteristics, the popularity of the category and the concentration of the category, can differently influence the app's performance and thus the diversification outcome of the developer. Our analysis of a panel data set of mobile apps on Google Play, the leading app store for Android mobile phones, provides support for the hypothesis. The results also show that the negative effect of category concentration overwhelms the positive effect of category popularity in influencing the performance of a newly released app as measured by number of downloads.

In chapter five, we conclude this dissertation by reviewing the summary of findings and their implications for platform business. The research questions studied in this dissertation provide

opportunities for further examining the competitive strategies in the world of platforms. We provide details of future works that will extend and address the limitations of this dissertation.

2.0 WINNERS-TAKE-SOME DYNAMICS WITHIN DIGITAL TECHNOLOGY MARKETS: A REEXAMINATION OF THE VIDEO GAME CONSOLE WARS

2.1 INTRODUCTION

Platform markets, where an intermediary facilitates transactions among two or more types of agents (e.g., complementors and consumers), have historically been competitive battlefields among platform owners. Typically, these competitions have yielded a dominant market leader who captures significantly more than 50% of the market share. In such markets, the eventual winner typically enjoys increasing returns to scale and high profitability. Thus, at the inception of such a market, platform owners attempt to rapidly expand the network on each side of the market, often at great cost (e.g., due to price subsidies). Managers have taken note of this process and are motivated to position their own products to become the winning standard in emerging platform markets (Eisenmann et al. 2006).

However, the expected outcome of a single platform owner achieving market dominance, the so-called “Winner-Takes-All” (hereafter “WTA”) result, has been challenged in recent platform market competitions. Instances of a different pattern of competition where no single winner emerges include the markets for digital flash memory cards, digital media files, digital image files and mobile operating systems (Bresnahan et al. 2015; Liu et al. 2012). In these markets, the competitions have not resulted in a single dominant winner, but rather a “Winners-Take-Some” (hereafter “WTS”) outcome, in which multiple platform owners survive the competition and each win a substantial, but non-dominant, share of the market.

Are these WTS results indicative of a change in the prevailing dynamics for platform markets such that WTA is no longer the expectation? Understanding whether a fundamental shift has occurred is of particular interest to managers involved in such markets. If WTA is not to be

expected, then the dominant strategy may call for less up-front subsidization and other costs associated with the attempt to win early market share. If WTS is now more likely to be the prevailing outcome for platform markets, then such technology platforms may need to be positioned to fight *in* the market (as with traditional products), rather than fighting *for* the market as managers of WTA products have been encouraged to do (Kemerer et al. 2013).

This research seeks to aid our understanding of whether fundamental changes in platform market dynamics are occurring. To that end, we empirically re-examine an oft-studied context that has resulted in numerous competitions over time: home video game console competitions. This market has followed a generational pattern, with new technology and new platform introductions resulting in numerous successive competitions. Further, these competitions, when consistently classified and analyzed, had, prior to the most recently concluded competition, yielded a single winner with dominant market share in each generational classification. Understanding why this most recent competition, unlike those that preceded it, yielded a WTS outcome illuminates our research problem, providing useful guidelines for adjusting expectations for both current and future platform markets.

The video game console market competitions are a useful context for study for other reasons as well. In addition to the clear economic value of the industry and its products — DFC Intelligence estimated the industry would surpass \$100 billion in 2018 (DFC Intelligence 2016) — the industry has been shown to be a useful specimen for examining a number of digital business-related topics, including network effects and complementary goods, as well as platform markets (Armstrong 2006; Caillaud and Jullien 2003; Economides 1996; Farrell and Saloner 1986; Gallagher and Park 2002; Katz and Shapiro 1985; Rochet and Tirole 2003). In addition, the cyclical nature of the industry, brought on by the rapid technological obsolescence of its

platforms, provides a number of natural experiments in a short period of time in which to study these phenomena.

In evaluating these competitions among video game consoles we observe an important change in complementors’ multi-homing behavior (i.e., development for more than one platform) that may have led to this recent WTS outcome. Multi-homing among video game developers has increased substantially — in the most recently concluded competition 65% of the most popular games were available on competitive consoles, the first competition in which this number has ever exceeded half of the market. We argue that this has contributed to the emergence of a WTS outcome in the most recently concluded competition.

The remainder of the paper is structured as followed. Section II reviews the literature on platform markets, multi-homing and research on video game consoles. In Section III we propose an objective schema for an analysis of video game platform market, as well as for the analysis of multi-homing in the Internet Class. We present a summary of our findings and discussion in Section IV, and Section V summarizes and suggests future research directions.

2.2 LITERATURE REVIEW

2.2.1 Platform markets

A *platform market* is a market in which an intermediary (the platform) enables interaction between two separate entities on at least two sides of the market¹ (Eisenmann et al. 2006; Katz and Shapiro 1985; Rochet and Tirole 2003) (See Figure 1). Examples of these markets include

¹ There is a significant amount of literature that describes this as a “two-sided market”. More current work identifies these as “platform markets”, an umbrella term which includes two-sided markets, and it is this current nomenclature that is used here.

PC operating systems (enabling interaction between consumers and application developers), employment websites (enabling interaction between job-seekers and employers), and video game consoles (enabling interaction between video game players and game developers) (Eisenmann et al. 2006). These markets are further characterized by the presence of positive *cross-side network effects*, by which the net utility on one side of the market (e.g., consumers of video games) increases as the number of adopters on the other side of the market (e.g., complementors such as video game developers) increases (Rochet and Tirole 2006). This creates a chicken-and-egg problem for platform owners who need to be attentive to both sides of the market in order to make their network grow (Rochet and Tirole 2003).



Figure 1. A Platform Market with Two-Sides

In evaluating the competitions within technology platform markets over the last few decades both academic research and marketplace results have fostered an expectation for the emergence of a dominant standard (Eisenmann et al. 2006; Gawer and Cusumano 2002; Katz and Shapiro 1985; Shapiro and Varian 1999). VHS, Microsoft Windows, eBay, PayPal, and Blu-Ray DVD are all examples of products that went on to dominate their respective platform markets. As has occurred in numerous networked markets, each example involved a season of conflict in which multiple, seemingly viable candidates contended for adopters before, finally, a single winner emerged with a dominant majority of the market share (Varian and Shapiro 1999). This trend of observing a WTA outcome, however, has been disrupted in some more recent competitions where no clear standard has arisen. Among flash memory cards, for instance, a number of formats initially competed, and multiple standards prevailed (Liu et al. 2012).

Similarly, on web pages, a number of image formats (e.g., .gif, .jpg, .png) can be found, with none of them holding a dominant share, and hence the emergence of a WTS outcome.

2.2.2 Multi-homing

Another key attribute of platform market competitions is the decision of adopters whether or not to multi-home, meaning they adopt more than one of the platforms engaged in a competition (Rochet and Tirole 2003). In a two-sided platform market both sides of the market (i.e., consumer and complementor) can choose to either single-home (i.e., adopt one and only one platform) or to multi-home. In the video game console context a consumer can choose to adopt only one console within a given competition (single-homing) or might instead adopt multiple consoles (multi-homing; e.g., can buy and use both an Xbox 360 and a PlayStation 3). Similarly, complement providers may single-home (by creating platform-exclusive content) or multi-home (by developing content for more than one competing platform)². This research shows that, where multi-homing costs are high, a single platform is more likely to win the market (WTA), and, where they are lower, a WTS outcome is more likely, all else being equal.

Prior economic literature has found multi-homing to be a significant factor in determining the price structure and dynamics of platform markets and their competitive outcomes. Rochet and Tirole (2003) found that when more buyers (i.e., consumers) multi-home, the result is a more favorable price structure for the sellers (i.e., complement providers) (Rochet and Tirole 2003). Armstrong (2006) argued that the decision of agents in a platform market to either single-home or multi-home is one of the determinant factors influencing the structures of prices offered to

² Some studies use *software exclusivity* or *software incompatibility* to refer to the opposite of multi-homing on the complementor side (i.e. here termed single-homing) (Corts and Lederman 2009; Lee 2013; Mantena et al. 2007)

both sides of the market (Armstrong 2006). Doganoglu and Wright argue that multi-homing makes firms less likely to make their network compatible, even when it is efficient to do so. Furthermore, although multi-homing can make compatibility more socially desirable, it makes it less likely for firms to choose network compatibility (Doganoglu and Wright 2006). Rysman found that when measured as holding credit cards from different networks (as opposed to using credit cards from different networks), multi-homing is more prevalent (Rysman 2007). Farrell and Klemperer describe how multi-homing practices weaken the network effects in different industries with two-sided markets, such as the market for video recordings, sound recordings and telecommunications (Farrell and Klemperer 2007).

Another factor that can weaken the network effects and make a WTS outcome more likely is the presence of low-cost conversion technologies (Liu et al. 2012). In the market of digital flash memory cards, no tipping to one format or standard was observed. This WTS outcome is attributed to wide adoption of converters acting as “gateway technologies” between multiple formats (David and Bunn 1988). The provision of converters reduces consumer perception of the value of network effects by allowing them to choose a flash memory card format with a smaller installed base without worrying about compatibility costs (Liu et al. 2012).

Most recently Bresnahan *et al.* show that in the two-sided market of mobile operating system platforms, the multi-homing of more attractive and highly demanded apps can cause a fragmented market structure, in other words, a WTS equilibrium (Bresnahan et al. 2015). Their model proposes that the non-tipping structure of the market can be explained by allowing for heterogeneity of app attractiveness to customers. The authors suggest that app demand is highly concentrated, and that a small subset of highly attractive apps will be in higher demand by customers, regardless of the platform. Due to high demand, such app developers find it

profitable to supply to both (or all) platforms and to multi-home across platforms. The model suggests that, if an adequate number of attractive apps multi-home, then the stable market structure will be in a fragmented equilibrium, i.e., a WTS outcome. The model is tested empirically with data collected on developers' platform choices and app and developer characteristics, as well as from commercial data on app usage. The empirical data supports this model, showing that since more attractive and highly demanded apps multi-home, the fragmented structure of the mobile app platform market is stable and no tipping will occur (Bresnahan et al. 2015)³.

2.2.3 Video game consoles

The video game console industry is a popular context for academic study (see Table 1 for a chronologically-ordered summary of video game console research), starting at least with Gallagher and Park's highly cited 2002 survey of video game console market dynamics in *IEEE Transactions on Engineering Management* (Gallagher and Park 2002)⁴. Other research has utilized the home video game console market context to investigate the platform success dynamics based on complement sales (Shankar and Bayus 2003), complement number and variety (Clements and Ohashi 2005; Srinivasan and Venkatraman 2010), complement quality (Corts and Lederman 2009; Iansiti and Zhu 2007; Zhou 2011), customer expectations regarding future complement availability and quality (Dubé et al. 2010; Iansiti and Zhu 2007), complement exclusivity (Lee 2013; Srinivasan and Venkatraman 2010), market concentration among

³ Bresnahan *et al.*'s observations about mobile applications' multi-homing behavior are further supported by recent work highlighting the software tools available to reduce the cost of this practice (Jiang 2016).

⁴ We note that some earlier research (e.g., Dermer 1992) also uses video game consoles as examples.

complements (Lee 2013), customer heterogeneity (Liu et al. 2010; Zhou 2011), and technical qualities of the platform itself (Derdenger 2014; Gretz 2010). In addition, the market has been used to assess the importance of platform technical qualities in determining complementors' market entry (Zhou 2011)⁵.

Prior studies have examined how the characteristics of the video games themselves (quality, popularity, and exclusivity) affect the market for video game consoles and its dynamics (Corts and Lederman 2009; Kim et al. 2014; Lee 2013; Prieger and Hu 2012). Historically, in the video game market multi-homing had not been a common practice since developing for multiple platforms meant re-programming games to work on those platforms, as well as incurring costs to manufacture and warehouse game cartridges. However, the composition of game development costs has changed, which can be hypothesized to increase the relative attractiveness for game developers to multi-home their games. Middleware “engines”, which enable developers to more easily and inexpensively replicate graphic rendering and game behavior across platforms, have become more common (Jiang 2016; Sherr 2013).

⁵ The home video game console market has existed since the early 1970s when various companies released home video game consoles (e.g., the Magnavox Odyssey). While the earliest consoles were limited to pre-loaded game content hard-wired into the console itself, in the mid-to-late-1970s console platforms, such as the Atari 2600 (VCS) began to appear. The functionality of these newer platforms could be extended through the purchase of additional complementary content (i.e., video game cartridges). Since then, video game consoles have formed a platform market, where manufacturers build and sell the console, while primarily third parties develop and sell games that can be played on that console (Rochet and Tirole 2003).

Table 1. Video Game Console Markets Literature Review

Author(s)	Title	Journal	Dependent Variable(s)	Platform Market Factors			
				Network Effects		Pricing/Subsidy	Other Concepts
				Buyer-Side	Seller-Side		
Gallagher and Park (2002)	Innovation and Competition in Standard-Based Industries: A Historical Analysis of the US Home Video Game Market	IEEE Transactions on Engineering Management	Market Winners (Anecdotal)	Discussed	Anecdotal	Price Cuts (Anecdotal)	Improvement in Graphics, Switching Cost
Shankar and Bayus (2003)	Network Effects and Competition: An Empirical Analysis of the Home Video Game Industry	Strategic Management Journal	Sales (in Dollars)		Sales of Top 10 Game Titles, Impact of Network Size		
Venkatraman and Lee (2004)	Preferential Linkage and Network Evolution: A Conceptual Model and Empirical Test in the US Video Game Sector	Academy of Management Journal	Complementor Decision to Develop for a Platform		(DV)		
Clements and Ohashi (2005)	Indirect Network Effects and the Product Cycle: Video Games in the US, 1994-2002	Journal of Industrial Economics	Units Sold	Cumulative Unit Sales (Prior to 1994)	Complementor Decision to Adopt Platform (Modeled)	Mean Console Price	

Zhu and Iansiti (2007)	Dynamics of Platform Competition: Exploring the Role of Installed Base, Platform Quality, and Consumer Expectation	Working Paper	Indirect Network Effects, Console Quality	Cumulative Unit Sales	Titles Available, Avail. of Future Titles, Gamespot Ratings	Mean Console Price	
Corts and Lederman (2009)	Software Exclusivity and the Scope of Indirect Network Effects in the US Home Video Game Market	International Journal of Industrial Organization	Number of Titles, Market Share	Cumulative Unit Sales	Titles Available, Number of "Hit Games"	Mean Console Price	Title exclusivity has increased over time and has weakened and changed the scope of indirect network effects
Chintagunta, Nair and Sukumar (2009)	Measuring Marketing Mix Effects in the 32/64 Bit Video Game Console Market	Journal of Applied Economics	Units Sold		Titles Available	Mean Console Price	
Dube, Hitsch and Chintagunta (2010)	Tipping and Concentration in Markets with Indirect Network Effects	Marketing Science	Market Share	Customer Valuation of Variety	Titles Available, Avail. of Future Titles	Console Price, Estimated Mfr. Royalty Fees	
Gretz (2010)	Hardware Quality vs. Network Size in the Home Video Game Industry	Journal of Economic Behavior & Organization	Market Share (Categorical), Available Titles	Market Share			Word Length, Processor Speed, RAM

Gretz (2010)	Console Price and Software Availability in the Home Video Game Industry	Atlantic Economic Journal	Console Price		Titles Available		
Liu (2010)	Dynamics of Pricing in the Video Game Console Market: Skimming or Penetration?	Journal of Marketing Research	Units Sold, Prices	Unit Sales	Titles Available	Mean Console Price	Consumer Heterogeneity (Modeled)
Srinivasan and Venkatraman (2010)	Indirect Network Effects and Platform Dominance in the Video Game Industry: A Network Perspective	IEEE Transactions on Engineering Management	Market Share	Cumulative Unit Sales	Titles Available, Title Genres Available	Mean Console Price	Game Title Exclusivity
Zhou (2011)	Bayesian Estimation of a Dynamic Equilibrium Model of Pricing and Entry in Two-Sided Markets: Application to Video Games	Working Paper	Console Units Sold, Software Units Sold, Market Entry		Online Software Ratings	Mean Console Price, Software Price	High- and Low-Type Consumers

Prieger and Hu (2012)	Applications barrier to entry and exclusive vertical contracts in platform markets	Economic Inquiry	Market Share	Market Share	Titles Available	Mean Console Price	Game Title Exclusivity and its impact on rivals' console demand
Lee (2013)	Vertical Integration and Exclusivity in Platform and Two-Sided Markets	The American Economic Review	Predicted Unit Sales, Consumer Welfare		Concentration of Sales ("Hit Titles " measured as being a Top 10 best-selling game)	Mean Console Price, Mean Complement Price	Prohibiting game title exclusivity contracts favors the incumbent
Kim, Prince and Qiu (2014)	Indirect network effects and the quality dimension: A look at the gaming industry	International Journal of Industrial Organization	size of installed base	Unit Sales	Quality-differentiated titles	Price cuts (Anecdotal)	Variety in Game Quality
Derdenger (2014)	Technological Tying and the Intensity of Competition: An Empirical Analysis of the Video Game Industry	Quantitative Marketing and Economics	Units Sold	Households with Units	Unit Sales and Revenue, Units per Household, Genre	Static Prices (Modeled)	Technical Features, Console as Game Producer

The video game console market is of particular interest in evaluating changing market dynamics. Since video game consoles are subject to rapid obsolescence due, in part, to their limited extensibility, a series of discrete platform competitions has emerged as new technology has been developed and brought to market. Thus each new competition begins with the rise of a new technology and ends with the onset of succeeding technologies (Gallagher and Park 2002). The resulting competitions have clear beginnings and ends, and each has a limited number of participants. Thus, the competitions themselves can be directly compared to each other to enable drawing inferences regarding the factors driving differences in competition dynamics.

2.3 ANALYSIS

2.3.1 Defining video game platform competitions

While these successive competitions have proven useful to researchers, the establishment of a consistently applied scheme by which to classify the generations of competitions has proven problematic. Although Gallagher and Park set out an initial classification scheme in 2002, many researchers have opted to draw from only a selected slice of market data, often without respect to boundaries around discrete competitions (Gallagher and Park 2002). Still others have invoked the concept of generations, without clearly citing the source of those categorizations. This is problematic in that understanding potential changes in dynamics among the various competitions will be less useful where there is not an agreed-upon set of competitors within any given competition.

Adding to the significant variation in competition classification schemes is the existence of a separate classification scheme on the widely-cited website Wikipedia, a scheme that neither coincides with classifications used in the academic literature nor presents the criteria used for

determining its own classification. As a result, between Wikipedia's popular classification and those conveyed by the academic literature, researchers and managers are left with a wide, inconsistent, and undocumented variety of ways by which the various video game consoles have been separated into discrete competitions (see Figure 2).

For example, the TurboGrafx console introduced in 1989 is characterized as "fourth-generation" by Wikipedia, but considered as "second generation" (along with earlier consoles, such as the 1985 Nintendo NES) in Gretz (Gretz 2010), as "third generation" in Gretz (Gretz 2010), and omitted entirely by Corts and Lederman (Corts and Lederman 2009). Similarly, the 1995 Sony PlayStation is considered as "fifth generation" by both Wikipedia and Corts and Lederman, but as "third generation" and "fourth generation" respectively in Gretz (Gretz 2010) and Gretz (Gretz 2010), and as "32-/64-bit generation" by both Chintagunta *et al.* and Dubé *et al.* (Chintagunta et al. 2009; Dubé et al. 2010). In addition, the Wikipedia classification scheme considers video game systems released prior to 1976 as the "first generation", whereas these non-platform devices (i.e., their functionality could not be extended through game cartridges, see Footnote 5) are disregarded by academic researchers.

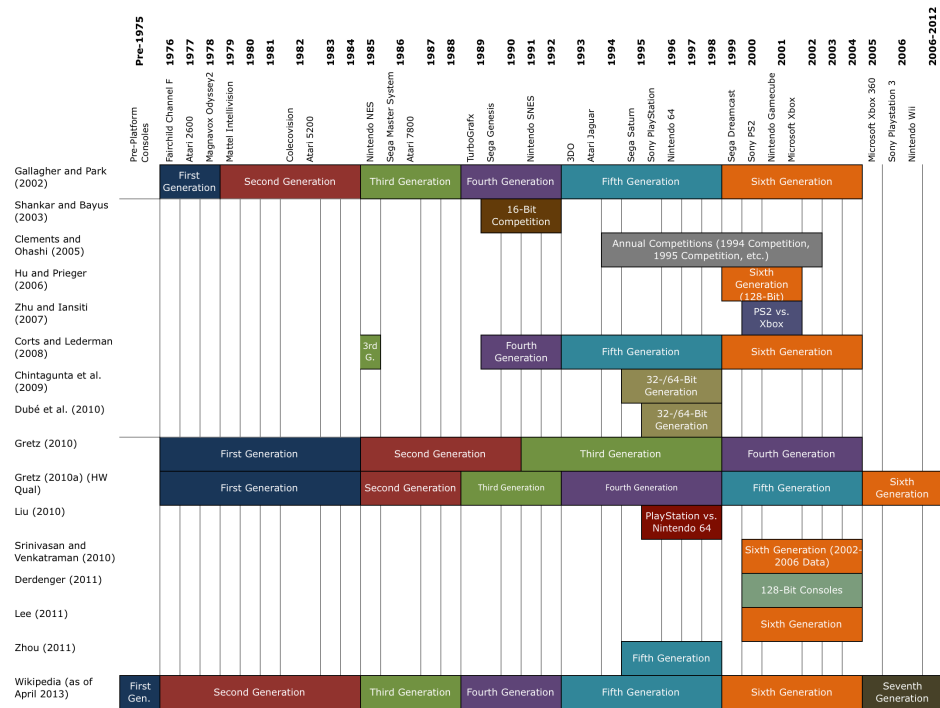


Figure 2. Comparison of Video Game Console Competition Classification Schemes

All of this raises the question as to which scheme is the most appropriate or suitable for research. These various existing categorization schemes are also problematic in that they can be difficult to replicate in terms of the criteria used to establish the boundaries. For example, the earliest of these studies, Gallagher and Park (2002), recounts the historical competitions in the video game console industry, identifying along the way six generations, with the onset of each new generation defined by the single requirement of a “100% improvement in graphics capability” (p. 70). This classification scheme has two limitations. First, there is no specific argument proposed as to why improvement in graphics capability is a sufficient and appropriate single criterion. Second, even if graphics capability is assumed to be the best single criterion, the measurement used to categorize a new generation is not specified, i.e., the concept of “100% improvement” in graphics capability is not defined in a manner that would allow independent replication.

A second problem with these competing classifications is that their results, in many cases, appear to be in sharp contrast to what has been observed in other network market outcomes, further undermining the trust that might otherwise be placed in them. In particular, two such contradictions stand out. The first is that prior theory in the evolution of technology markets and the importance of network effects and complementary goods suggest that markets such as the home video game console market should be expected to have WTA outcomes in which a single dominant standard emerges from amongst a field of competitors (Arthur 1989; Katz and Shapiro 1985; Utterback 1996). However, the Wikipedia generational classification, as a recent instance of these discordant prior classifications, fails to yield this expected result. For example, Wikipedia's fourth generation does not end with a single competitor having over 50% of the market. This anomalous result would have the potential to be of significant interest to management of technology scholars and to practice if there could be greater confidence in the underlying classification scheme, which is, unfortunately, undocumented.

Another anomaly from these schemes arises from the considerable research and empirical evidence from Christensen and others, which indicates that true generational shifts are the result of disruptive technologies, and that a winning vendor in one generation is very rarely the winning vendor in the succeeding generation (Christensen 2011; Henderson and Clark 1990). For example, as technology progressed over time, the rigid disk drive industry was able to build ever-smaller hard disk drives, establishing a number of standards along the way. With the onset of each new generation of hard disks (i.e., a new size standard), however, Christensen found that the dominant firm in one generation did not come to dominate the succeeding generation (due to focusing too acutely on the highly profitable generation in which it dominated). Similar histories

have been attributed to the computer and PC industry (Christensen 2011) and to the photolithography industry (Henderson and Clark 1990).

The Wikipedia classification scheme contradicts this prior Christensen and related research as it includes the Sony PlayStation in its fifth “generation” and the Sony PlayStation 2 in its sixth, which results in the same competitor winning successive competitions. Again, like the anomalous fourth generation result cited above, this outcome also has the potential to be a managerially interesting finding, if it were only based on a reliable, rigorously established, and well-documented categorization.

2.3.2 A rationalized classification scheme

The lack of a coherent classification scheme and the anomalous conclusions resulting from the Wikipedia generation summary and others suggest the need for an improved classification scheme that is unambiguously described and can be consistently applied to past, present, and future home video game console competitions. We propose a scheme that meets these criteria. Further, we note that when looking at past competitions, our scheme rectifies the discord between existing approaches to classification and theoretical expectations for competitive outcomes in past competitions.

Our scheme is based on both a primary and a secondary classifier. The primary classifier is processor word length and, within this, the second classifier is time between world-wide release dates. The logic behind this approach is two-fold. First, processor word length has been a widely used technical metric to define computing power (Babb and Terry 2013). Processors with longer word lengths, all else being equal, will have superior operational performance relative to shorter word length machines (Corts and Lederman 2009), and these benefits have

resulted in a monotonic growth path for processor word length. Growth in processor word lengths is also a potentially disruptive force in that systems software (e.g., operating systems) often requires significant modification in order to take advantage of the new longer word length offered by the hardware. Therefore, an incremental increase in processor word lengths is a natural technical break point between what we term *classes* of consoles⁶.

Second, we recognize that word length, although a useful metric, may not capture all of the technical advancements that take place, particularly in periods where improvements in word length happen more slowly. Therefore, we add a second dimension to the classification criteria that is based on the time between world-wide release dates. The passage of time as a criterion should capture the “residual”, i.e. the incremental technical improvements that naturally occur over time and that would not be fully captured by processor word length. It also has the advantage that it is likely to continue to be a useful metric in analyses of future consoles, unlike, perhaps, a more locally technology-specific metric, such as a measure of display technology that may become outdated.

Specifically, we consider a new class to begin when a system is introduced with a processor with a longer word length (e.g., 64-bit consoles are considered a different class from 32-bit consoles), and then additionally where there has been a gap of at least two years between the world-wide releases of major consoles⁷. This second criterion results in splitting each of the

⁶ We have adopted the terminology of “class” rather than “generation” to convey the notion of improvement from one group to the next, and to avoid the confusion with prior work that could result from adding one more discordant set of “generations” to the literature.

⁷ By “major” we include consoles that sell at least one million units; the million-unit sales figure has been a traditional threshold, e.g., Crossley, Rob. 2013, February 19. “Timeline: The Towering Triumph of PlayStation 2”, *Computer and Video Games*.

<http://www.computerandvideogames.com/391986/features/timeline-the-towering-triumph-of-playstation-2/>.

original 8- and 16-bit sets of consoles into multiple classes. The resulting full classification of consoles and data regarding sales and class dominance can be found in Figure 3 and Table 2⁸.

Authors' Scheme	Proto-Class	Pre-Platform Consoles	Pre-1975																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																							
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Figure 3. Authors' Proposed Classification Scheme

This new classification scheme results in nine measurable classes of consoles (excluding the earliest pre-platform consoles) that cover the entire period from the 1970s to the consoles of the most recently completed competition.

2.3.3 Past competitions and WTA outcomes

In contrast with earlier proposals, the classification scheme presented in Figure 3 is consistent, clearly explicated, and more easily replicable. It is also applicable to the entire video game console history, rather than being limited to a subset of years like most of the schemes shown in Figure 2. Beyond these desirable measurement characteristics, it also produces a different set of dominant consoles (“winners”) than would be yielded by some earlier classification systems.

⁸ Sales figures given are current world-wide unit sales as of Sep 2016. Sources: Wikipedia (Fairchild Channel F, Magnavox Odyssey2); http://images.businessweek.com/ss/06/10/game_consoles/source/3.htm (Atari 2600) <http://www.intellivisiongames.com/history.php> (Intellivision) <http://www.colecovision.dk/history.htm> (Colecovision); http://www.mashpedia.com/Atari_5200 (Atari 5200); <http://retro.ign.com/articles/965/965032p1.html> (Sega Master System) http://www.gamasutra.com/blogs/MattMatthews/20090526/1521/Atari_7800_Sales_Figures_1986_1990.php (Atari 7800); <http://www.gamepro.com/gamepro/domestic/games/features/111822.shtml> (TurboGrafx-16); <http://segatastic.blogspot.com/2009/12/mega-drive-sales-figures-update.html> (Sega Genesis); and vgchartz.com (Nintendo NES, Late 16-Bit, 32-Bit, 64-Bit, 128-Bit and Internet Classes).

Two important findings emerge from applying this classification scheme to earlier video game console competitions. First, the results of this approach make evident that a single, dominant console emerges in each class, as highlighted by bold text in Table 2. This is consistent with much prior widely accepted research on technological market evolution, which predicts single winners (Katz and Shapiro 1986). Second, this classification scheme yields results in which winners do not repeat from one competition to the next, which, again, is predicted by existing literature (Christensen 2011; Henderson and Clark 1990; Utterback 1996). Finally, we note a significantly different finding for the most recently concluded competition, the Internet Class competition, wherein a single winner did not arise. This new result will be explored in greater detail in the data analysis section below.

Table 2. Classification of Video Game Console Competition Classes

<i>Note: WTA dominant console for each class denoted in bold.</i>					
Class	Console	Word Length or Elapsed Time	Release Date	Sales (M)	% of Class
Early 8-Bit	Fairchild Channel F	8 Bits	Aug-76	0.8	2.2%
	Atari 2600	8 Bits	Oct-77	30	83.8%
	Magnavox Odyssey2	8 Bits	1978	2	5.6%
	Mattel Intellivision	10 Bits ⁹	1979	3	8.4%
Middle 8-Bit	Colecovision	8 Bits	Aug-82	6	85.7%
	Atari 5200	8 Bits	Nov-82	1	14.3%
Late 8-Bit	Nintendo NES	8 Bits	Oct-85	61.9	78.7%
	Sega Master System	8 Bits	Jun-86	13	16.5%
	Atari 7800	8 Bits	Jun-86	3.8	4.8%
Early 16-Bit	NEC TurboGrafx-16	16 Bits	Sep-89	10	20.1%
	Sega Genesis	16 Bits	Sep-89	39.7	79.9%
Late 16-Bit	Nintendo SNES	16 Bits	Aug-91	49.1	100.0%
32-Bit	3D0	32 Bits	Oct-93	2	1.7%
	Atari Jaguar	32 Bits	Nov-93	0.5	0.4%
	Sega Saturn	32 Bits	May-95	8.8	7.6%
	Sony PlayStation	32 Bits	Sep-95	104.3	90.2%
64-Bit	Nintendo 64	64 Bits	Sep-96	32.9	100.0%
128-Bit	Sega Dreamcast	128 Bits	Sep-99	8.2	3.9%
	Sony PlayStation 2	128 Bits	Oct-00	157.7	74.3%
	Nintendo GameCube	128 Bits	Nov-01	21.7	10.2%
	Microsoft Xbox	128 Bits	Nov-01	24.7	11.6%
Internet Class	Microsoft Xbox 360	4 years ¹⁰	Nov-05	85.6	31.3%
	Sony PlayStation 3	6 years	Nov-06	86.6	31.7%
	Nintendo Wii	5 years	Nov-06	101.2	37.0%

2.3.4 The transition to WTS

We term the most recently completed competition the “Internet Class” competition. It began with the release of the Microsoft Xbox 360 in November 2005. Its competitors, the Nintendo Wii and Sony PlayStation 3, were both released worldwide in November 2006. Industry expectations were that this competition would end with a single winner as had previous competitions, with

⁹ This oddity has been confirmed at the manufacturer’s website: <http://www.intellivisionworld.com/English/FAQ/>. Including this unique console configuration with its contemporary peers in the Early 8-bit Class, despite the disparity in word length, does not materially affect the results, given its low sales.

¹⁰ This class is designated through Rule 2 (i.e., the number of years between major releases).

many industry pundits predicting an eventual victory for one or another of the platforms. For example, in 2007, the research firm *Research and Markets* predicted that the PlayStation 3 would be the eventual winner (Berardini 2007), whereas *Wired* magazine projected a victory for Nintendo's Wii (Beschizza 2007). In 2008 Don Reisinger at *CNet* claimed that Microsoft's Xbox 360 would win (Reisinger 2008)¹¹.

Based on their chosen strategies the manufacturers of these consoles also appeared to believe that the Internet Class competition would yield a WTA result. Microsoft, for instance, hoped to gain an edge by being the first to release their platform, blaming their failure to dominate the previous, 128-bit class in part on conceding a full year of sales to the eventual winner, PlayStation 2 (Morris 2005). In the third year of the competition, Microsoft seemed to continue to believe that a WTA result would occur, pointing out in a press release that it had been the first to reach 10 million unit sales in the United States and that, according to one senior vice president, "History has shown us that the first company to reach 10 million in console sales wins the generation battle" (Mcwhertor 2008). However, despite this head-start, and an early lead in sales, by the end of 2007 (the first full year in which all three consoles were available) the Xbox 360 had lost its lead in worldwide sales (Babb and Terry 2013) (see Figure 4).

In fact, at the end of 2008 it looked as though the Internet Class competition might instead tip toward Nintendo, as at that point the Wii installed base share had grown to 48.6%. This trajectory, together with the expectation of strong network effects as had been witnessed in past competitions, bolstered the idea that the Wii would become the competition's dominant platform.

¹¹ Note that industry observers predicted a WTA outcome, although was no general agreement on which console would win.

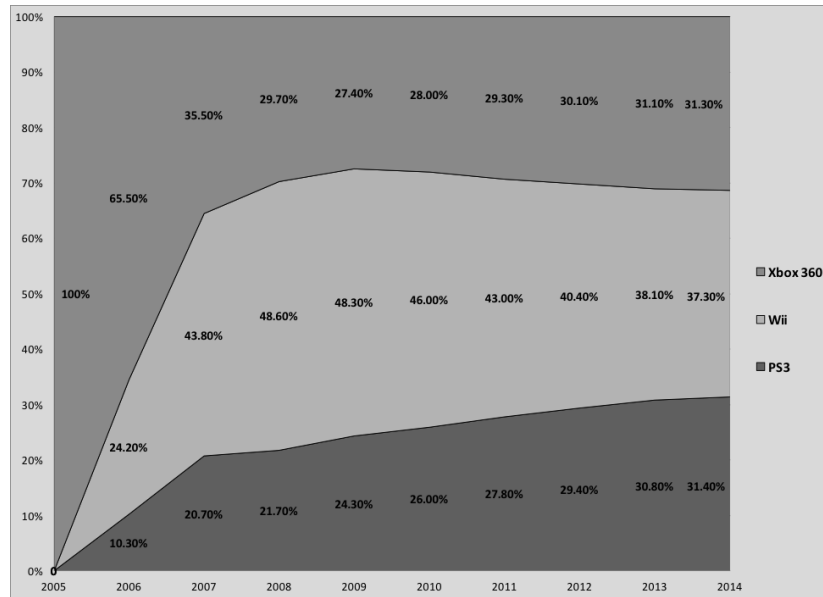


Figure 4. Percentage of Worldwide Installed Base by Platform by Year, Internet Class

That dominance, however, never occurred. Despite its lead in installed base, Wii's market share fell every year after 2008. In 2011, more units of each of the PlayStation 3 and Xbox 360 were sold than of the Wii. By the end of 2012, while Nintendo's console retained a larger installed base than its two competitors, none of the three could claim 50% of the market (see Figure 4). Given that this competition is now over, we note that, unlike those that preceded it, it did *not* result in a WTA outcome but rather a three-way WTS outcome. In the next section, we discuss this anomalous result and evaluate multi-homing's contribution to this outcome.

2.3.5 Influence of multi-homing

2.3.5.1 Multi-homing measurement

Given the findings of recent work within the mobile phone app context (Bresnahan et al. 2015), where multi-homing behavior of the most popular apps was seen to influence competition outcomes, we now examine whether multi-homing behavior by complementary products contributed to the historically anomalous WTS outcome seen in the most recently concluded competition.

In particular, Bresnahan argues that it is the multi-homing decisions of those complements deemed *most valuable to the user*¹² that are instrumental in determining a platform competition's result. Their model allows for the heterogeneity of the value to the user among complements, and assumes that the higher value apps make a larger contribution to the attractiveness of the platform to the user, all else being equal. The decision by such high value complements to multi-home can sustain a WTS market outcome. Given that video game platform complements are primarily video game content, we focus on the video games that can be seen as the high value complements. In the video game industry game critique websites, such as IGN.com, GameSpot.com, GameCritics.com, and GameRankings.com publish reviews, rankings and scores for games, giving a measure of the value for the investment the users will make when buying a game (Stuart 2015). These professional video game critics are found to have a greater influence on buyers' decisions than other consumers' opinions, and higher review scores are found to lead to higher sales (Cox and Kaimann 2015). Therefore, consistent with this prior work, we believe that it is appropriate to treat these ratings as a useful measure of user value.

¹² Bresnahan *et al.* use *popularity*, *attractiveness* and *value to the user* somewhat interchangeably. To avoid confusion with other specific popularity measures in use we will generally refer to this concept as “value to the user”.

Given our ultimate research focus on the relative success of console platforms, we need to specify what qualifies as multi-homing for the purpose of our analysis. Each game may have been released on only one platform (i.e. single-homing) or on more than one platform (potentially multi-homing). Within the context of this analysis, *we consider a multi-homing game one that was released on multiple platforms in the same class*. Our definition of multi-homing is therefore more specific than prior videogame research where an exclusive game has been defined as one that has never been released on any other platform, regardless of class (Corts and Lederman 2009). Under our definition if a game is released on only one platform in a given class competition then it is single-homing within that competition, regardless of whether it is also released for a platform (or platforms) engaged in a different class competition. Again, we take this measure since we are concerned only with the outcomes of discrete competitions defined by classes; therefore, the fact that a game may also later be released on a platform in a future class cannot affect the outcome of the current class in question. In order to restrict the analysis of multi-homing to a given competitive class we exclude the games that are released after the competition in a given class is settled. We use a consistent cutoff date of December 31st of the year in which the first video game console of the next class is in the market. This is to ensure that a multi-homing game is, in fact, influencing the market outcome before the competition of the current class ends.

In addition, our study, following Bresnahan *et al.*, also differentiates between *multi-homing* (at the time of a complementary good's introduction) and *late multi-homing* (Bresnahan et al. 2015). *Late multi-homing* is described as an instance where a complement is ported to a second platform, but, due to the delay in availability on multiple platforms, it can no longer be influential on whether the market tips (Bresnahan et al. 2015). Given the relatively short cycle

times for each class in the video game context, we consider it an instance of late multi-homing *when it takes more than six months for a complement to become available on a second platform*. In analyzing the impact of multi-homing on platform success it is appropriate to restrict the analysis of multi-homing to a given competitive class¹³.

Previous video game studies which looked at software exclusivity considered them retrospectively and cross-sectionally, such that if a given piece of software (e.g., video game, mobile app, etc.) had ever been available on more than one platform, it is considered multi-homing (Corts and Lederman 2009; Lee 2013). However, in the economics multi-homing literature there are documented instances where a delay in multi-homing has made it uninfluential on the market outcome (Bresnahan et al. 2015) (Farrell and Klemperer 2007). Therefore, we specify that for a multi-homing game to be relevant the gap between release dates on the first platform and the second platform must be less than six months¹⁴. This differentiation is important in the context of video game consoles due to the generational pattern of this market. If a game is ported to a second console long after the dynamics of competition in that class have taken shape, such a delay means that multi-homing cannot influence the market outcome.

¹³ We also conducted a sensitivity analysis using a longer lag time, and the main results were unchanged.

¹⁴ This is unless the second platform has entered the market more than six months after the release of the game. In that case, the gap between the release date of the *game* on the second platform and the market entry of the second *platform* needs to be less than six months. It should be noted that sensitivity analysis was also done using an alternative one year gap size, and those results are consistent with the six month gap.

2.3.5.2 Multi-homing behavior of the top *MobyRank* games

MobyGames¹⁵ is a comprehensive source for video game data that has been used previously in academic studies (e.g., Corts & Lederman 2009). Its content includes video game ratings offered from professional critics and other respected reviewers whose work appears in various media outlets (e.g., online, television, print) (“MobyGames FAQ” 2014). Based on its assembly of third-party reviews, MobyGames assigns each game a “MobyRank”, which is a measure of collective critical opinion and critical success. This rank is based on a weighted average of normalized rankings from the various reviews collected, and requires the availability of a minimum number of critical ratings. In prior research meta critic scores similar to MobyRank are found to be a determinant of sales performance, e.g. high scores were found to be a determinant of a game becoming a blockbuster, and a proxy for the utility derived by the player (Cox 2014). We therefore use MobyRank as a measure for video game user value.

Review Source	Review Date	Rating	Normalized Rating
Game Over Online	Nov 22, 2010	80 out of 100	80
Hey Poor Player	Dec 08, 2010	★★★★☆	80
Gamers Daily News	Nov 24, 2010	7.5 out of 10	75
GamePro (US)	Nov 19, 2010	★★★★☆	70
Softpedia	Dec 20, 2010	7 out of 10	70
Gamereactor (Sweden)	Nov 22, 2010	7 out of 10	70
IGN	Nov 19, 2010	6 out of 10	60
videogamer.com	Nov 26, 2010	6 out of 10	60
Eurogamer.net (UK)	Nov 26, 2010	3 out of 10	30
1UP	Nov 26, 2010	D	25

Figure 5. Critic Reviews for a Sample Game on MobyGames (Source: MobyGames.com¹⁶)

¹⁵ <http://www.mobygames.com/>

¹⁶ <http://www.mobygames.com/game/xbox360/crazy-taxi>

Figure 5 depicts a sample of critic reviews for a game with multiple sources of critics. MobyGames also presents a list of the “most popular” games for each platform. We use the MobyRank measure of games within this most popular set to identify the highly valued games. Appendix A provides a detailed list of the games considered. We collected data on the highest MobyRanked games for each platform in the following classes: Early 16-bit class, 32-bit class, 128-bit Class, Internet Class (See Table 3).¹⁷ We collected the game title and MobyRank for these most popular games for each console.

¹⁷ We do not include Late 16-bit class and 64-bit class in this analysis as there is only one platform in each of these classes and therefore it would not be possible to examine multi-homing across platforms. In addition, in the Internet Class, we exclude Wii since compared to PS3 and Xbox 360, Wii is lacking in technical and graphical capabilities (Bakalar 2009). Given the introduction of the Wii remote, Wii differs from Xbox 360 and PlayStation 3 in the audience it attracts and its most popular genres (Marchand and Hennig-Thurau 2013). Wii does not support HD and its hardware is not on a par with either the PS3 or Xbox360. Xbox 360 and PS3 both have CPUs working at 3.2 GHz, while the microprocessor of a Wii console operates at 729 MHz. The Wii has significantly less main system RAM (64 MB compared to Xbox 360's 512 MB shared RAM and PS3's 256 GB). PS3 and Xbox360 are also superior and faster to Wii when it comes to GPU: the GPU clock speed for Xbox 360, PS3 and Wii are 500 MHz, 550 MHz and 243 MHz respectively. Xbox 360 has 512 MB of shared video RAM and PS3 benefits from 256 MB of video RAM, while the Wii uses 24 MB of video RAM (Thurrott 2010). These technical differences make it essentially technically infeasible and therefore very unlikely for PS3 and Xbox 360 games to be available on Wii, and vice versa. For the same reason, other studies have also excluded Wii when analyzing the competition in this class (Rietveld et al. 2016).

Table 3. Video Game Consoles and Classes Included in the Most Popular Games Dataset

Class	Video Console	# of games with release dates
Early 16-bit class	TurboGrafx	151
	Sega Genesis	158
32-bit class	3DO	113
	Atari Jaguar	59
	Sega Saturn	144
	Sony PlayStation	183
128-bit Class	Sega Dreamcast	171
	Sony PS2	202
	Nintendo GameCube	193
	Microsoft Xbox	189
Internet Class	Microsoft Xbox 360	169
	Sony PlayStation 3	137

Next, we rely on *Gamewise* for data on the release dates for the popular games. *Gamewise* contains data on more than 45,000 games and offers a searchable database¹⁸. *Gamewise* contains release data of videogames on the different platforms for which each game has been released. From this source we were able to collect release dates for 80% of MobyGames-rated most popular games¹⁹ (Table 3). In the event that a game on a platform is released on different dates in different regions, we collect the first release date on that platform. The collected data set from these two sources contains, for each game, the platform(s) for which the game was released, the release date on each platform, and its MobyRank.

¹⁸ See <http://gamewise.co/> and <http://gamewise.co/about/>

¹⁹ Twenty percent of the games do not appear in the Gamewise.co database of the games, or the database lacks complete data on their release dates. However, these games are less likely to appear in the top-ten or top-20 games, and therefore their omission is unlikely to affect the results.

Using these data we present the results for the top-ten popular games with the highest MobyRank for each platform in each class²⁰. For example, in the Early 16-bit class we find the ten games with the highest MobyRank on TurboGrafx and on Sega Genesis. We label each of these games as either multi-homing or single-homing. The results (Table 4) show that only ten percent of these twenty games (top-ten on two platforms) are multi-homing (i.e. only two highly ranked games in the Early 16-bit class are available on multiple platforms).

Table 4. Level of Multi-homing among top-ten highly MobyRanked games

Class	% of multi-homing games
Early 16-bit class	10%
32-bit class	20%
128-bit Class	43%
Internet Class	65%

Table 4 shows that the percentage of games that are multi-homing increases from this mere 10% level to 65% in the Internet Class competition, or more than half of the games. In prior studies regarding dominant design emergence, a dominant design has been defined as when 50% or more of products all share the design (Benner and Tripsas 2012). Analogously, we propose that when the level of multi-homing among the most highly valued complements exceeds the 50% threshold, that this leads to a WTS platform market.

²⁰ Note that the result shown also holds if a different threshold is used, e.g. top-20 games, rather than the traditional top-10 (Lee 2013).

2.3.5.3 Multi-homing behavior of the top *GameRankings* games

To increase our confidence in the results and allow us to focus further on the change in multi-homing between the 128-bit and Internet Classes, we next collect an alternative set of ranking data from a different source, *GameRankings*. Similar to MobyGames, *GameRankings* aggregates review scores for games from both online and offline sources²¹. Using these sources they compile lists of all-time top-ten best games for each platform in the 128-bit and the Internet Classes²². We follow the same procedure to identify the multi-homing games in each class and observe the change in the levels of multi-homing between two classes (Table 5).

Table 5. Level of Multi-homing among all-time best games

Class	% of multi-homing games
128-bit Class	33%
Internet Class	50%

We see here a result similar to that offered using the MobyGames data, thus confirming an increase in multi-homing from the 128-bit to the Internet Class among the highest rated games available in each of those classes. This corroborates the idea that a shift in multi-homing behavior among the highest valued complements has helped drive the WTS result in this most recently completed competition.

²¹ See <http://www.gamerankings.com/> and <http://www.gamerankings.com/help.html>

²² Historical data on *GameRankings* is not available for all platforms in the early 16-bit and the 32-bit classes

2.3.5.4 Multi-homing behavior of the top *VGChartz*-selling games

Additionally, we also consider actual complement sales as a proxy for user value, a measure that determines which complementary goods' multi-homing decisions might influence a competition's outcome. Data were collected on the top-ten best-selling games for all consoles in the 128-bit and Internet Classes from *VGChartz.com*, an industry research firm that publishes data and estimates related to game hardware and software sales²³. Using release date data from Gamewise, and using our same multi-homing criteria, we identify multi-homing games and measure the percentage of multi-homing among the top-ten best-selling games in each class (Table 6).

Table 6. Level of Multi-homing among top-ten best-selling games

Class	% of multi-homing games
128-bit Class	18%
Internet Class	60%

We observe here an even greater increase in the levels of multi-homing between the 128-bit and the Internet Classes when complement value, as measured by sales, is considered. These results show that 60% of the top-ten best-selling games for the platforms in the Internet Class are multi-homing, as opposed to only 18% of such games multi-homing in the prior 128-bit class.

²³ <http://www.vgchartz.com/about.php>. Historical data for classes earlier than these two were not available on this site. A sensitivity analysis shows that these results also hold true for alternative thresholds, e.g. top-20 games.

2.3.5.5 Additional sensitivity analyses

In identifying the most highly valued games we followed the prior literature that has relied on a top-ten list (Lee 2013). Here, we test the robustness of our results using an alternative criterion, i.e. the top-20 games. Table 7 shows the result of analyzing the data on the top-20 most popular games with the highest MobyRank and the top-20 best-selling games per *VGChartz*. The pattern of change in the levels of multi-homing is consistent with the previous results on the top-ten games²⁴.

Table 7. Level of Multi-homing among Top-20 MobyRanked and VGChartz Games

Class	Top-20 MobyRanked Games	Top-20 VGChartz Games
Early 16-bit Class	7%	N/A
32-bit Class	15%	N/A
128-bit Class	51%	23%
Internet Class	62%	55%

As a second sensitivity analysis, and to further explore the observed increase in multi-homing in the Internet Class, we performed an analysis using an alternative gap size of one year between the release dates to tag a game as multi-homing (as opposed to the six-month gap used to differentiate late multi-homing in the previous analyses). Applying this new specification across all three data sources yielded the results shown in Table 8 for the ten games with (a) the highest *MobyGames* ranking, (b) the highest *GameRankings* rankings, and (c) the best-selling games per *VGChartz.com*.

²⁴ Similar sensitivity analysis is not possible using the *GameRankings* data since *GameRankings* compiles lists of all-time top-ten best games only.

Even with this more generous definition of concurrent multi-homing the observed patterns of change remain consistent with previous results and show a meaningful increase in the level of multi-homing in the Internet Class compared to previous video game console classes.

Table 8. Level of Multi-homing among top-ten games with one year gap size, across game-ranking sites

Class	Top-ten MobyRanked Games	Top-ten GameRanking Games	Top-ten VGChartz Games
Early 16-bit Class	10%	N/A	N/A
32-bit Class	25%	N/A	N/A
128-bit Class	48%	43%	20%
Internet Class	65%	55%	60%

Third, we test for the sensitivity of our results using an alternative, stricter measure of multi-homing. This alternative measure adds a stricter criterion for labeling a game as multi-homing by examining the specific platforms the game is available on. In this analysis, a game is labeled as multi-homing if it meets the previously described criteria and is also released on the dominant video game console of that class. For example, the game “Flashback: The Quest for Identity” released on the Atari Jaguar in the 32-bit class is also available on the 3DO console, but not on the Sony PlayStation, which was the market winner of this class. Therefore, under this alternative stricter measure it would not be considered multi-homing. The results of the analysis using the stricter measure are shown in Table 9. We observe that, consistent with prior results, the level of multi-homing has been steadily increasing over time.

Table 9. Level of Multi-homing among top-ten MobyRanked games using stricter measure of multi-homing

Class	% of multi-homing games
Early 16-bit class	10%
32-bit class	13%
128-bit class	38%
Internet class	N/A ²⁵

In another sensitivity analysis, we consider the possibility that for the games released in the holiday season, the multi-homing decision may have a stronger influence on competition outcome. This is because the games released in the holiday season receive more attention and demand from the users, and some users may decide to purchase a video game console only due to the exclusivity of the hottest game released in the season. To account for this effect, we use a smaller gap size of three months for the games released in the month of November. The result for the games among top-ten highly MobyRanked games is presented in tables 10. The results remain either unchanged or consistent with the main results.

Table 10. Level of Multi-homing among top-ten MobyRanked games using a smaller gap size for holiday season games

Class	% of multi-homing games
Early 16-bit class	10%
32-bit class	15%
128-bit Class	43%
Internet Class	60%

Additionally, we turn our attention to the release time of the games, to evaluate how far along in the competition the games are released. The premise here is that the games that are released towards the end of a cycle of competition may be less influential in the WTS outcome. To this end, we perform the analysis, using the six-months gap size, for the games released

²⁵ The level of multi-homing using the alternative measure based on a dominant platform cannot be computed for the Internet Class because there is no single winner in this class.

before the competition has reached its mid-point. Also, we perform the analysis by only including the games that are released before two-thirds of the time of the competition between platforms has passed. The results are presented in tables 11 and 12. The results remain consistent with the main findings, showing that the level of multi-homing has been steadily increasing over time.

Table 11. Level of Multi-homing among top-ten MobyRanked games for the games released before mid-point of competition

Class	% of multi-homing games
Early 16-bit class	5%
32-bit class	20%
128-bit Class	43%
Internet Class	60%

Table 12. Level of Multi-homing among top-ten MobyRanked games for the games released before two-third-point of competition

Class	% of multi-homing games
Early 16-bit class	15%
32-bit class	23%
128-bit Class	48%
Internet Class	65%

All of these sensitivity analyses support the initial results of an increasing level of multi-homing of video games over time. In the next section, we discuss the implications of this observed change and how it supports a WTS outcome for the Internet Class video game market.

2.4 DISCUSSION

2.4.1 Summary of results

The emergence of a dominant leader with a substantial majority of the market share has typically been the observed outcome in platform markets. But, in more recent competitions, there have been occurrences of an alternative outcome in which there are multiple winners, each with some relevant market portion (Liu et al. 2012). Understanding the underlying mechanism that results in such a change in the dynamics of market should be useful to managers as it helps to guide appropriate strategies for firms to better position their products and services. To better compare the classes of video game consoles and to address the conflicts between different classifications of consoles, we proposed a new, objective classification scheme to define the discrete platform competitions. The scheme is based on two classifiers: processor word length and time between world-wide release dates. Using the new, objective scheme enabled us to appropriately determine the results of the competitions in each class, which shows an unprecedented, “no-tipping” WTS outcome in the Internet Class.

Prior literature has emphasized the importance of multi-homing, especially among highly valued complementors, and how multi-homing can influence whether or not a market tips toward any one platform. We collected and analyzed three sets of data to examine whether developers of the most highly valued video games in the Internet Class are releasing their games on multiple platforms at a higher rate than they did in previous classes. We started by analyzing the data on highest MobyRanked games for each console in four consecutive classes and found that multi-homing rose from 10% to 65% from the Early 16-bit Class to the Internet Class. Using an alternative data source, we performed a similar analysis to compare multi-homing behavior among the highest rated games of both the 128-bit and Internet Classes, which confirmed our

original finding. We also considered game sales as a measure and again witnessed the same outcome, where the games with the highest sales multi-homed substantially more in the Internet Class competition than the 128-bit class, up to 60% of the top-ten most popular games (from 18%). We also confirmed the robustness of our results by testing with different samples (e.g. top-20 rather than top-10) and varying the gap size (from 6 months to one year).

2.4.2 Implications

The increase in the level of multi-homing among the highest quality and most popular games is associated with the emergence of an unprecedented WTS outcome in the Internet Class of video game consoles. Reports from industry show the prevalence of multi-homing among the most popular games in the Internet Class even in 2013, which was the last year the Internet Class consoles competed against each other. According to a report from the *Wall Street Journal (WSJ)* at the end of the Internet Class in 2013, the three games that revitalized the video game industry before the release of the next-class consoles were “Grand Theft Auto V”, “Madden NFL 2015” and “NBA 2K14” (Sherr 2013). Looking at the data available on these games it is interesting (but now not surprising) to see that all of these games are multi-homing in the Internet Class, consistent with the results of our study.

While the presence of a single dominant platform has the potential to benefit all members of a market, it is also the case that complement providers (e.g., video game developers) have a counter-incentive to actively promote the survival of multiple platforms. Intuitively, in a market with a monopolistic platform, that platform has considerable leverage in negotiating the licensing fees it receives from game sales, while with multiple platforms this is diminished, all else being equal. When there are multiple viable, successful-enough platforms, game developers have a

stronger negotiating position and may opt to develop for all, a subset, or only one of the competitors. In earlier competitions, this preference may have been offset by significant costs; developing for multiple platforms means re-programming games to work on those platforms as well as, in the pre-digital downloads days, incurring costs to manufacture and warehouse products. However, technology and practices have changed such that more of the initial costs incurred when writing a game for its first platform are now avoidable in making the game available on a second platform. The *WSJ* reported that new software tools have reduced the amount of repetitive work needed to make games, and this new layer of automation saves both time and money for game developers (Sherr 2013). For instance, in the past decade game publisher Electronic Arts has been devoted to enhancing the game engines that are described as “dynamic workhorses”. The game engines provide tools to game developers, making game development more efficient and enabling more cost-effective cross platform development (Needleman 2016)²⁶. In addition, past versions of Xbox and PlayStation consoles used very different hardware chips, which increased development time to create two sets of software. However, in the Internet Class, they used the same chip.

Additionally, given the incentives to do so, including reduced porting costs, much of the economic rent in the videogame industry may have shifted from the platform owners to the game developers (Dao and Zmud 2015). Sales of “blockbuster” games suggest that game makers are indeed reaping the benefits of this shift²⁷. Further evidence was admitted by Nintendo president

²⁶ Similar to the middleware engines used in video game development, cross-platform development tools for smartphone applications can also reduce the required effort for application development. These tools allow for creating apps for different operating systems using the same base code (Ohrt and Turau 2012)

²⁷ “In Video Game Market, Blockbusters’ Dominance Grows”, *New York Times* BITS, September 30, 2013

Satoru Iwata, who said that widening games' availability threatened the existence of Nintendo, which has relied on its exclusive access to its games to sell its consoles (Negishi 2013).

In the Internet Class, competition reduction in the cost of game development may have also been a function of downloadable content, which provides revenue opportunities to help offset multi-homing costs. The in-game purchases of downloadable content are a source of revenue for both downloadable games and games purchased in physical format. This enables the game developers to realize further income from the same general game and code base, thus helping to offset multi-homing costs in the Internet Class. Further, information regarding the downloadable content is easily obtained via the Internet and it facilitates a consumer's decision-making on purchasing such content (Lim et al. 2012). The transition to making games Internet-compatible and the consoles Internet-ready started with consoles in the 128-bit class, although these were limited in the age of relatively slow dial-up modems (Collins 2000). In fact, the chance of success for the Internet connectivity feature was questioned by contemporaneous observers partly because the fulfillment of transactions required a high-speed broadband infrastructure that could support widespread Internet access and high-volume information transmission, which took time to develop (Takahashi 2000). Therefore, despite the fact that consoles like the PlayStation 2 were capable of connecting to the Internet, it was speculated that Sony had to wait until its next class of consoles (i.e., PlayStation 3) before its online ambitions could be realized (Dawson 2000). However, with advances in networking technology and the widespread availability of faster Internet services, Internet-enablement became standard for consoles in the Internet Class, and games and game content can be downloaded onto consoles without the use of physical media. Both PlayStation 3 and Xbox 360 included far more extensive connections with the Internet than their predecessors (Guth et al. 2005).

Sony and Microsoft are also changing their focus to achieve increases in service revenues such as subscription and downloadable games (Needleman and Mochizuki 2016). This follows the change in consumers' habits to increasingly buy and download video games over the Internet (Sherr 2014). Electronic Arts, for example, announced in 2014 that sales and game downloads over the Internet made up 45% of the company's revenue, and this was expected to reach 50% in 2015 (Sherr 2014). Earlier in 2013 the president of Nintendo also stated that Nintendo was under pressure to change its console-focused business strategy due to the prevalence of downloadable games that can move seamlessly between platforms (Negishi 2013).

In addition to the increased availability of downloadable games, the video game console market has witnessed a surge in the supply of free-to-play games. Free games offered on websites have been a source of revenue since the 1990s, when advertisers incorporated products directly into games (Barnes 2002). In the video game console market the free-to-play games are available without an initial purchase, but the in-game purchases make these games a source of revenue. The increase in market revenue of the free-to-play games that are offered in downloadable form started in the Internet Class, and it has been on the rise since 2010. The expansion of downloadable games and the proliferation of free-to-play games allow game developers to benefit from the same code base on multiple platforms and from gaining revenue from in-app purchases (Negishi 2013). These additional revenue opportunities make multi-homing more feasible for game developers.

A change in the generational nature of the video game console market may also be reflecting the observed change in dynamics of the market and the high potential for emergence of a WTS outcome. Recently the *WSJ* reported that, instead of introducing a new generation of consoles after several years, Sony and Microsoft will be releasing modest hardware upgrades

more frequently (Needleman and Mochizuki 2016). Sony released a hardware-upgraded successor to the PlayStation 4 in November 2016; this successor is still branded as a PlayStation 4 and is compatible with the earlier version. The *WSJ* further reported that Microsoft is expected to follow suit in late 2017. Neither of these two new releases is considered a next-generation console, but rather consoles that are compatible with the PS4 and the Xbox One, but with faster Graphic Processing Units (GPUs) (Baker 2016). This is in contrast to the industry-wide pattern for console makers to release their next console about every five years (“No Laughing Matter” 2001). Since there does not seem to be a large technological leap from the current class of consoles to their successors, this sort of backward compatibility can help console makers to take advantage of their already existing installed base (Claussen et al. 2010). Given the prevalence of multi-homing among the most popular games, the backward compatibility can intensify the impact of such games on the market outcome.

2.4.3 Conclusions and future research

In this research, we have reexamined the platform market for videogame consoles and their complementary videogames. Using a new objective measurement scheme we identify a series of classes of videogame platforms, for which all but the last exhibit classic Winner-Takes-All (WTA) outcomes and all exhibit the Christensen-like propensity for incumbents in one class to be replaced by a new entrant in the succeeding class. In the last completed class, the Internet Class, a Winners-Take-Some (WTS) outcome has been observed, and, as suggested by recent economics research, this is also the class where a high level of multi-homing of its complements was observed. Contemporaneous news accounts point to declining multi-homing costs in this

environment related to software engines and downloadable media, and these can reasonably be assumed to have contributed to the multi-homing outcome.

While the differences between the Internet Class video game console competition and earlier competitions are clear, they lead to the more broadly interesting question of whether these differences represent a more general shift in digital goods markets. Prior research in flash memory, graphics formats, and apps for mobile operating systems have shown that all of these are also demonstrating a tendency towards WTS equilibria. Future empirical research could be usefully devoted to other platform markets that may exhibit similar changes, such as application software in non-mobile operating system environments and streamed or otherwise downloadable digital consumer media that have supplanted fixed physical format complements. Similar changes in these environments would suggest that managers re-consider market strategies that have been honed based on the WTA outcomes of past market competitions.

3.0 USER ENGAGEMENT IN DIGITAL PLATFORMS: A FIELD EXPERIMENT

3.1 INTRODUCTION

A digital platform, powered by the Internet and connected users, is a networked ecosystem that facilitates the interaction between multiple market participants cohabiting the ecosystem (Choudary et al. 2013). By orchestrating the supply and demand, digital platforms facilitate the exchange of physical goods (e.g., Amazon, e-bay), services (Uber, Airbnb), or information goods (Netflix, Spotify).

The performance and the success of platform companies are often measured through metrics such as the number of users, the volume of facilitated transactions, and the revenue generated (Enders et al. 2008). Platforms can follow different strategies to gain revenue such as imposing transaction fees on exchange of physical goods or services, charging subscription fees to grant access to the platform and/or the content, and sale of advertising. It is expected that with the success in acquiring and retaining participants on both the demand and supply sides of the platform, increasing users' willingness to pay, and enabling more successful interactions, more revenue is generated (Enders et al. 2008; Gallagher et al. 2001). Additionally, since the platforms create value by enabling the interactions between the demand and supply side participants, their success relies on not only acquiring users, but to encourage and facilitate their engagement with the platform. Besides, with higher levels of use and engagement, users' valuation of and loyalty to the platform increases, which creates a barrier to switching to alternative platforms. Therefore, another important measure of success is the amount of engagement platforms can solicit from their participants (Slaney 2011). When users are willing to invest in a platform by giving it their attention, they are bound to spend more time on and

engage more with the platform. The users' participation and engagement with the platform can therefore be a key driver of success.

Paying attention to user engagement is even more important for platforms that enable the exchange of information goods (e.g. movies, music, news) as compared to those enabling exchange of physical goods or services. Platforms enabling the exchange of physical goods (e.g., e-bay, Amazon) strive for brokering more transactions, having sellers sell more and getting users to make more purchases. On platforms that provide a service (e.g., Uber, Airbnb), the goal is to get users to request a service more frequently. In contrast, the platforms that enable the exchange of information goods push for increasing the viewership and the engagement on the platform (Verhage 2016). Similar to many digital content providers, BuzzFeed, a social news website, considers the number of unique visitors or page views as an outdated success metric. Instead, the company considers metrics that can measure engagement as more important (Ingram 2016). For example, content providers track "attention-minute," which measures the "engaged-time" of users (Ingram 2014). Digital content provider platforms follow numerous strategies to encourage and increase user engagement. Adding new features, for example, worked very well for Instagram (the mobile photo-sharing application with nearly 700 million active users). Introducing Instagram Stories –pictures and videos that disappear after 24 hours- as a new feature greatly increased the engagement-to-follower rate on the photo-sharing platform, as users were provided with a new way of interacting with each other (Constine 2017).

Since information goods are often experience goods, the information about the product is better obtained through experiencing it rather than searching for information. For such products, a consumer's behavior greatly relies on guided sampling based on recommendations (Nelson 1970). Platforms that provide information goods can therefore facilitate guided sampling and

provide recommendations to get users to consume more and to spend more time on the platform. Platforms rely on implementing recommendation systems to enable content discovery and increase user engagement. YouTube, the world's most popular online video community, relies heavily on personalized recommendations to facilitate content discovery and keep users entertained and engaged (Arora 2016; Davidson et al. 2010). Likewise, some platforms rely on including social features in the design to increase engagement. Spotify, a leading music streaming platform, allows its users to follow artists and other users on the platform learn what they are listening to (Katz 2012). Moreover, platforms attempt at providing appropriate information signals (in the form of reviews, ratings, etc.) that can lead to higher content user engagement and discovery. Recently, Netflix transformed its ranking system from the five-star ratings to a simple thumbs up and thumbs down, aiming at simplifying and increasing the rating activity of its users. The input from users is then used to develop and present users with a “percentage match” informational signal, that can help them discover contents that match their taste (Molina 2017).

Despite the practical relevance of monitoring user's engagement for platforms, a rigorous examination of the factors that influence user engagement in the research literature is still scarce. Extant studies have mostly focused on ways to increase number of adopting users (Bapna and Umyarov 2015), users' willingness to pay (Dou et al. 2013) , amount of content consumption (Sanjeev Dewan et al. 2017), and firms' revenue and profit (Jiang and Guo 2015). The exceptions are some recent works, which study the effectiveness of design and information signals on users' engagement, search experience and discovery (Amblee et al. 2017; Yi et al. 2017). Yi et al examine how the design of social commerce platforms can influence users' search experience and decision satisfaction. By offering two types of social product search cues

(product tags and socially endorsed people), this study focuses on how the search experience can be improved in terms of the diagnosticity and serendipity (Yi et al. 2017). Yi et al define diagnosticity as users' perception of how helpful a website is in helping the user to evaluate the relevant products in a search process, and define serendipity as the users' perception of how helpful a website is in helping a user discover products beyond their original expectation. But what still remains unanswered is how digital content provider platforms can influence the search behavior and discovery of their users that will increase the user's engagement with the platform. Therefore, it is important for IS literature to focus on design features that can help platforms achieve the goal of increased user engagement.

Prior research suggests that design features and informational signals are helpful to platforms in engaging their users, enabling desirable user behavior, and increasing revenue (Aral, Dellarocas, et al. 2013; S Dewan et al. 2017; Godes et al. 2005).. To this end, studies have looked at effect of incentive schemas (Aral, Muchnik, et al. 2013), active-personalized referrals and passive broadcast notification (Aral and Walker 2011), features that facilitate peer endorsement and referrals (Dou et al. 2013), social product search cues (Yi et al. 2017), among others. Particularly, as the availability of information signals (in the forms of ratings, reviews, or aggregated consumption metric) is expected to create social influence, some studies have focused on the effect of these informational signals on sales (Moretti 2011; Svedic 2015; Yang et al. 2012), amount of consumption (Amblee and Bui 2007; Sanjeev Dewan et al. 2017; Zhou and Duan 2016), and search costs (Amblee et al. 2017). However, there is a gap in our understanding of how these informational signals can improve user engagement. Further, the effect of informational signals has mostly been studied contingent on only presence or absence of them (Amblee et al. 2017; Amblee and Bui 2007; Sanjeev Dewan et al. 2017). The information

signals, however, may have other influential attributes such as whether the signals are aligned with each other (conveying consistent information to the user) or in conflict with each other (conveying conflicting information to the user). To examine the interplay between the two information signals, we aim at answering the question of how the conflict between these signals can influence user engagement.

In this study, we focus on how availability and conflict of information signals like ratings and reviews can influence and improve user engagement. We build on prior studies to examine how users can be motivated by information signals like ratings and reviews to explore content (Amblee et al. 2017; Yi et al. 2017). We draw on information foraging theory (IFT) and the social information foraging model (SIF) to examine how information signals can influence search behavior of users and lead to more user engagement and improved discovery. IFT proposes a model that explains the cue-following behavior of an information-seeker in the task environment. The information is dispersed in patches and the information scent and search cues can help the information forager effectively search in the environment and collect valuable information. SIF complements IFT by considering the situations where a (diverse) group of information-foragers cooperate and engage in social exchange of information (hints). (Pirolli 2009; Pirolli and Card 1999). SIF suggests that when individuals are offered heterogeneous hints, their sense-making is improved and the likelihood of high-valued discoveries is increased. Analogously, when the platforms provide users with information signals, it enables sharing information and hints between information-seekers by disseminating information to them. Therefore, this study aims to address the following research questions:

- 1) *How does the availability of information signals influence user engagement on online content platforms?*

2) How does the availability of conflicting information signals influence discovery on online content platforms?

We investigate our research objectives in the context of music streaming platforms. Like other platforms, the mission of a music streaming platform is to facilitate the interactions between its participants: the music consumers and the music artists. On the music streaming platforms, music consumers can browse and search catalogs, gain access to a wide variety of songs, and “stream” music they like. On the other side of these platforms are the music artists, relying on music streaming services to reach out to a bigger audience, gain revenue and make a strong fan base. By connecting the two sides of this market, music streaming platforms are helping the music industry recover after two decades of decline in revenues due to piracy and falling prices. Being the music industry’s fastest growing revenue source, the US streaming music platforms accounted for about 66 percent of the music industry revenue in 2017, showing a continuous growth similar to 2016. (Friedlander 2018; Shaw 2016).

In the music streaming marketplace, multiple platforms are competing to attract users and gain revenue from ads and subscription fees. As such, the number of subscribers is one of the most commonly used metrics to compare the success of these platforms. While the number of subscribers (and free users) is one measure of success, it is also important to consider the extent to which those users are engaged with the platform (Constine 2015). More engagement with the platform by spending more time or creating numerous playlists makes the platform more valuable to the user and creates a switching cost. User engagement is typically measured by the number of hours users spend on the platform, the number of playlists created by the users, and the number of the streams of the songs (Statista 2013). Music discovery also is very important to keep users engaged with the platform (Admirand 2015). Music discovery occurs when a music

listener is uncertain about the music s/he wants to listen to, and browses an available music collection to discover new music (Bogdanov et al. 2010). Engaging in music discovery entails spending time to discover, adding new songs to playlists and discovering diverse songs.

Recognizing the importance of music discovery, music streaming platforms have taken action to facilitate this aspect and they take pride in their discovery credentials. Spotify offers its users a personalized weekly playlist every Monday morning, “Discover Weekly”, to bring new discoveries matching the users’ listening profile (Spotify 2015). Following suit, Apple Music started releasing a weekly mix every Friday, called “My New Music Mix”, to offer music discovery (Perez 2016). In addition to offering curated playlists to facilitate discovery, it is also vital for platforms to understand how they can influence users’ behavior in terms of music discovery and engagement by managing social interactions and facilitating spread of information (Aral, Dellarocas, et al. 2013; Godes et al. 2005). In this study, we examine how music streaming platforms can improve user engagement and diversity of discovery by providing users with information signals.

This paper is organized as following. In the next section, we review the theoretical framework and propose our hypotheses. Section 3.3 describes our research methodology. In section 3.4 we discuss our data collection and provide summary of results. Conclusion and discussion on the findings of this study are presented in section 3.5.

3.2 THEOREICAL DEVELOPMENT

In this section, we first draw on the digital platforms literature to shed light on why monitoring metrics related to user engagement is important for digital content provider platforms. Next, we

review prior works that have looked at the effect of designing with social features and offering information signals on improving the outcome variables of interest for platforms. Then we draw on information foraging theory (IFT) and the social information foraging model (SIF) to address the gap in our understanding and hypothesize on how the availability and conflicting information signals influence user engagement and discovery.

3.2.1 Platform Markets

A platform market is characterized by the interaction of at least two sides of a market (the complementor and the consumer) through an intermediary (i.e. the platform) (Katz and Shapiro 1985; Rochet and Tirole 2003). In recent years and with wide spread adoption of the Internet, the platform business model has been widely adopted to enable the interaction between market participants over the Internet, such as digital content providers (enabling interaction between content owners and content consumers). For a platform to achieve success, not only is it important to get customers and complementors adopt the platform, but it is also important to get them to use the platform. This is due to the presence of indirect network effects on platforms, where the gain for an agent on one side is commensurate with the number of agents on the other side (Farrell and Klemperer 2007; Katz and Shapiro 1985). Another successful competing strategy for a platform is to create a switching cost for its consumers. Platforms can create features that in turn lead to potential switching costs for customers. Categories of switching costs include transaction cost, cost of learning the new brand and the psychological cost incurred due to brand-loyalty (Klemperer 1995). Additionally, platforms can compete with each other by leveraging the value of data and enhancing the platform design. For example, platforms can utilize data on user behavior and test the performance of and optimize particular features. Data

analytics can significantly help the platform company invest in design and greatly increase the value generated for users and the company. The optimization of features can further assist the platforms, enhance the platform design, and facilitate interactions (Parker et al. 2016).

Digital content provider platforms also focus on the design of their platforms and the quality of tools they provide to compete. For example, design of a recommendation system that can provide utility to users and the platform have received a lot of attention both in the industry (Arora 2016; Katz 2012) and in the academic literature (Bogdanov et al. 2010; Davidson et al. 2010; Knees and Schedl 2013). But beyond the starting point of a corpus of content curated by the recommendation system, it can help platforms further keep their users engaged by enabling them to explore and discover content. As users become capable of discovering content, they are more likely to use the platform more frequently and consequently their level of engagement increases. Additionally, with more use and engagement, consumers' switching cost increases, which further helps platforms gain a competitive advantage. Aral et al suggest that the IS literature can focus on employing social design and features to answer the question of how platforms can invoke user engagement and enable desired user behavior. In this study, we aim at answering this question.

3.2.2 Social design

As an increasing number of platforms are integrated with social networks, it becomes crucial to examine how platforms can view this integration as a key resource and understand its potential to create more value. An important consequence of incorporating a social network into platforms is the increased opportunity of social interactions among users, both at the same sides of the platform and across. As social interactions are found to influence a user's behavior, it is up to

platforms to decide how they can leverage this influence to achieve their goals by managing the social interactions. Godes et al. (2005) suggest that firms can benefit from social interactions by actively fostering and managing them. Possible actions are shaping the social network, facilitating the spread of information and imposing how and to whom information will be disseminated.

Aral et al. (2013) further discuss how businesses are being transformed by social media and social networks. They propose a taxonomy of dimensions along which IS research can focus to answer the question of how platforms can use social networks to create value. The framework introduces four categories of activities to describe how social media can be leveraged: design and features, strategy and tactics, management and organization, and measurement and value (Aral, Dellarocas, et al. 2013). Our study fits within this framework by filling the gap in our understanding of social media and business transformation in the areas of “design and features” and “measurement and value”. In the area of “design and features”, we contribute to the literature on how specific features and designs help platforms attract users, create engagement, enable and constrain user behavior, and increase revenue. Additionally, in the area of “measurement and value”, we contribute to a body of work that has mostly focused on the relationship between social media and consumer choice in purchase context by looking beyond purchases and measuring the value of social media in influencing users’ engagement and discovery.

3.2.3 Social influence

There is a rich body of literature on how firms and platforms can exploit social design and features to achieve their goals and create value (Table 13 provides a summary of representative

studies). Similar to Aral et al's observation (Aral, Dellarocas, et al. 2013), in our survey of prior works we see a focus on measuring the added value of social design mainly in influencing consumer's decision in the adoption and purchase contexts. Aral and Walker examine the effectiveness of using two viral design features, active-personalized referrals and passive-broadcast notifications, on a peer's adoption decision in the context of Facebook applications. They find that for the users facing viral product design features implemented in the application, there is an increase in the rate of application adoption by peers (Aral and Walker 2011). Another study in the context of online music-sharing platforms examines the effect of an individual's adoption of the premium subscription on her peers' adoption decision. Bapna et al (2015) find that the effect of peer influence is significant, leading to an increase in peers' adoption of the premium service. In the purchase and consumption contexts, Dou et al (2013) analytically model and evaluate the effectiveness and the trade-off between word-of-mouth strategies, seeding and building social media features, on user's willingness to pay in the context of paid digital goods. Proposing another analytical model, Jiang and Guo (2015) examine the effectiveness of review system design decision of rating scale cardinality on users' perception of ratings and product sales. The result of the analytical model cautions the firms about considering the characteristics of the products (product valuation and mainstream level) and consumers (misfit cost) when designing a rating system.

Table 13. Literature review on platforms's use of social design

Authors	Title	Journal	Dependent variable(s)	Independent variable(s)	Context	Method
Liu (2006)	Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue	Journal of Marketing	Movie sales	volume and valence of WOM	Digital goods (movies)	Empirical (secondary data)
Amblee and Bui (2007)	Freeware Downloads: An Empirical Investigation Into the Impact of Expert and User Reviews On Demand for Digital Goods	AMCIS Proceedings	Number of downloads	availability of either or both expert reviews and user reviews	Digital goods (freeware)	Empirical (secondary data)
Zhu and Zhang (2010)	Impact of Online Consumer Reviews on Sales : The Moderating Role of Product and Consumer Characteristics	Journal of Marketing	Product sales	Online reviews moderated by product characteristics (popularity) and consumer characteristics (Internet experience)	Video games	Empirical (secondary data)

Chakravarty, Liu and Mazumdar (2010)	The Differential Effects of Online Word-of-Mouth and Critics' Reviews on Pre-release Movie Evaluation	Journal of Interactive Marketing	Evaluation of a movie	Availability and valence of two information source: critic's review and word-of-mouth	Digital goods (movies)	Lab experiment
Gray, Salvatore and Iyer (2011)	Innovation impacts of using social bookmarking systems	MIS Quarterly	level of individual's personal innovativeness	Number of times social bookmarks are accessed, number of people whose social bookmarks an individual accesses, diversity of people whose social bookmarks an individual accesses	Social bookmarking system	Empirical (using secondary data and survey data)
Aral and Walker (2011)	Creating Social Contagion Through Viral Product Design: A Randomized Trial of Peer Influence in Networks	Management Science	Adoption response of peers	Availability of viral features: active-personalized referrals and passive-broadcast notifications	Facebook application	Randomized field experiment
Fong (2012)	Targeted Marketing and Customer Search	NA-Advances in Consumer Research	Consumer exploration and discovery	Personalized targeted marketing	Retail	Field experiment

Yang, Kim, Amblee and Jeong (2012)	The heterogeneous effect of WOM on product sales: why the effect of WOM valence is mixed?	European Journal of Marketing	Product sales	Volume and valence of WOM moderated by the product characteristics (mainstream vs. niche)	Digital experience goods (movies)	Empirical (using archival and secondary data)
Aral, Muchnik and Sundararajan (2013)	Engineering social contagions: Optimal network seeding in the presence of homophily	Network Science	Peer's product adoption	Availability of either or both WOM strategies: seeding and incentive	Digital product adoption	Simulation and empirical
Dou, Niculescu and Wu (2013)	Engineering optimal network effects via social media features and seeding in markets for digital goods and services	Information Systems Research	Willingness to pay	Seeding and building social media features into digital products	Paid digital goods (e.g. professional social network, dating sites)	Analytical modeling
Bapna and Umyarov (2015)	Do Your Online Friends Make You Pay? A Randomized Field Experiment on Peer Influence in Online Social Networks	Management Science	Peer's subscription to premium service	Individual's receiving of a subscription to premium service as a gift moderated by peer's network size	Music-listening social network	Randomized field Experiment

Jiang and Guo (2015)	Design of Consumer Review Systems and Product Pricing	Information Systems Research	Review outcomes and product sales	Review system design decisions: rating scale cardinality, showing granular reports; moderated by the product characteristics (product valuation and mainstream level) and consumer characteristics (consumer misfit costs)	e-commerce	Analytical modeling
Zhou and Duan (2016)	Do Professional Reviews Affect Online User Choices Through User Reviews? An Empirical Study	Journal of Management Information Systems	Number of downloads	The interplay between two WOM sources: professional reviews and user reviews	Online software market	Empirical (secondary data)
Yi, Jiang and Benbasat (2017)	Designing for Diagnosticity and Serendipity: An Investigation of Social Product-Search Mechanisms	Information Systems Research	Perceived diagnosticity and serendipity of search experience, decision satisfaction	Availability of social product search cues: product tags and socially endorsed people	Social-networked-based product-search website	Lab experiment

Dewan, Ho and Ramaprasad (2017)	Popularity or Proximity: Characterizing the Nature of Social Influence in an Online Music Community	Information Systems Research	Number of song plays	Availability of either or both information signals on popularity in the community and among friends	Online music community	Quasi-experiment
Amblee, Ullah and Wonjoo (2017)	Do Product Reviews Really Reduce Search Costs?	Journal of Organizational Computing and Electronic Commerce	Search cost measured as time spent on task and cognitive effort, decision confidence	Availability of either or both editorial reviews and customer reviews	Information search and decision making	Lab experiment

Furthermore, many studies have looked at the effect of availability of information signals from different sources of online word-of-mouth on consumers' evaluation of products and product sales. In the context of movie sales, Liu (2006) studied the effect of volume and valence of word-of-mouth from forum message boards on box office revenue and investigated its dynamic effect in the pre-release and the early weeks of opening. Liu found that volume but not the valence of WOM offers significant exploratory power for box office revenue. Amblee and Bui (2007) tested the effect of availability of either or both expert reviews and user reviews on the number of downloads of freeware in the digital goods context and found that the existence of the signals increase the number of downloads but the valence of reviews does not matter. To further examine the contextual factors moderating the effect of word-of-mouth, Yang et al (2012) proposed and tested the moderating role of product characteristics (mainstream vs. niche). They examined how the volume and valence of WOM affect sales of movies. They found that volume of WOM has positive and greater effect on sales for mainstream movies than niche movies. The effect of valence of WOM is also positive but it is greater for niche movies than mainstream movies. In more recent work and in the context of online music communities, Dewan et al (2017) investigate the effect of availability of information signals from two sources of word-of-mouth, the popularity in the community as a whole (popularity influence) and the popularity among an individual's peers (proximity influence). They found that both information signals increase the number of plays when offered separately, but that proximity influence dominates the effect of popularity influence when both are available.

3.2.4 Search experience: user engagement

While there has been a plethora of studies on how social design in general and online word-of-mouth in particular affect outcomes in purchase and adoption contexts, little attention has been paid to the emerging outcomes of interest for content platforms such as user engagement and discovery. For online platforms, generating revenue from subscription fees is fundamental (Gallaughier et al. 2001) and therefore the number of subscribed users is an important measure of success. Additionally, purchase or consumption behavior measured as willingness to pay, product sales or amount of consumption can also positively influence profit and revenue. However, due to the importance of emerging metrics such as user engagement and discovery for online content platforms, it becomes vital to further investigate the behavior of users. It raises the question of to what extent subscribed users engage with a platform and explore its content. In the case of consumption, it is important to investigate whether consumers are exploring and diversifying their consumption.

In a recent study, Yi et al (2017) investigated how design can influence the search experience of users. They examined the effect of availability of two social product search cues: product tags and socially endorsed people on users' search experience. The two outcome variables of interest focused on the search experience are perceived serendipity, defined as the extent to which a website helps finding useful but unexpected content, and the perceived diagnosticity, defined as the extent to which a website is helpful in effectively accessing and evaluating relevant products. This study found that the presence of tags increased perceived serendipity and diagnosticity of search experience. In another recent study, Amblee et al also focused on the search behavior and examined how availability of either or both editorial reviews and customer reviews influence search costs (both in terms of time spend and cognitive effort

required). They found that the availability of either of these information signals reduce search costs but when both are available, the search cost is not reduced. However, decision confidence is boosted with simultaneous availability of these two signals. We contribute to this body of research by improving our understanding of how social design and information signals through word-of-mouth can influence and improve user engagement and divergent and serendipitous discovery. To this end, we build on prior studies that have examined the effects of word-of-mouth and we draw from information foraging theory (IFT) and the social information foraging model (SIF).

3.2.5 Information foraging

IFT models the information seeking behavior of an information forager in the task environment. The information is often dispersed in patches in the environment, and the information scent from each patch help the forager evaluate the profitability and prevalence of information source. In the absence of information scent, the forager has to perform a random walk in the task environment. In the presence of information scent, scent-following behavior is dynamic and if the scent is strong enough, the forager can make correct decisions and maximize the discovered information (Peter Pirolli and Card 1999).

The information foragers in a task environment may also cooperate and share information with each other that can help each individual increase their finding of discovered information. This cooperation between the information foragers is particularly important given the rise of the Internet, Web 2.0 and mobile communications. Information foraging has become a social task which involves many interacting users actively foraging and sharing information, rather than a being solo foragers. Borrowing insights from structural hole theory and examining the network

of the foraging users, Pirolli explains that when a user is connected to diverse and densely connected clusters, he is in a brokerage position and has an advantage of exposure to greater diversity. The brokerage position is contrary to a position where an information forager is surrounded by homogenous opinions, viewpoint and information resource. The homogeneity of received information is likely to produce redundant findings (Pirolli 2009). Social foraging theory (SIF) builds on the notion that when a group of differing information foragers cooperate and engage in social exchanges of information (or hints), they bridge across content areas and information social groups. In such settings, individuals cooperate and exchange information with different networks. Sharing of heterogeneous hints is expected to improve individual's sense making and foraging and increases the likelihood of discovering useful information.

In a recent study, Yi et al draw on IFT and SIF to explore the effect of social design on consumer's search experience (Yi et al. 2017). They examine the influence of social design on the diagnosticity and serendipity of users' search experiences. In this study, we build on studies that have examined effects of online word-of-mouth as an example of information signal and examine its effect on a user's search experience. Since online word-of-mouth has been found to influence consumer's choice, we expect that it can effectively work as an information scent and guide the user in the task environment. Therefore, we examine how information signals influence user's information search and outcome in online content platforms. In particular, in this study we examine the effect of two types of information signals that have been found to influence amount of consumption in online content websites (Sanjeev Dewan et al. 2017), namely the popularity of content in the community as a whole (popularity on platform) and popularity of content among peers (popularity among peers). Drawing from the SIF, we hypothesize that availability of information signals in the forms of popularity on platform and popularity among peers will

create a strong scent that can guide the user in the task environment. By making these two popularity information signals available, the platform is implicitly facilitating the sharing of the hints from other information foragers (users), which SIF suggests will increase the discovery on the platform.

Additionally, when popularity on platform and popularity among peers are both present, these two information signals can be in conflict with each other, influencing the user's search behavior. Dewan et al did not find an interaction between the two signals. However, they only allow for interaction of the two signals with regards to their presence and absence. The SIF model suggests that when the user receives heterogeneous information hints, the scent becomes stronger as it breaks the homogeneity and redundancy of the hints. This further enables the information forager to explore and find valuable music. In this study, we are examining whether conflicting information signals can work as heterogenous information hints and increase a user's engagement and discovery on the platform. Thus, we hypothesize that:

H1a: All else equal, users exposed to conflicting information signals have higher levels of platform engagement than users exposed to aligned information signals.

H1b: All else equal, users exposed to conflicting information signals have higher levels of platform engagement than users exposed to no information signals.

3.3 RESEARCH METHODOLOGY

To test our hypotheses, we deploy a randomized between-subject field experiment to collect real user behavior for a real-world music platform. We manipulate the independent variable (i.e. availability of conflicting information signals). As the dependent variable, we are measuring the user's engagement and discovery on the platform.

3.3.1 Field experiment setting

We test our hypotheses on a social platform mobile application, Rapchat, where users can record their own songs and also explore and find songs created by other users. The users on this platform are both content creators and content consumers. Since the users as content consumers do not have prior familiarity with the content creators or the available content on the platform, it is crucial for this platform to invoke and increase discovery of content. The app is designed to encourage discovery of songs and artists by having a discovery tab where users can find songs and artists. (Figure 6 and Figure 7). This feature makes this app an appropriate setting for our study to investigate how such platforms can improve user engagement and discovery. The app also offers the functionality of users following each other's profile on the platform and creating a social network. The possibility of forming a social network on this platform allows for creation of popularity information signal among a given user's social network, making this platform suit our experimental needs. This mobile application has more than 120 thousand monthly active users. The social networking feature is used extensively: 57% of the users follow at least one other user and 36% of the users have at least one follower. An average user follows 24 other users and has 36 followers.

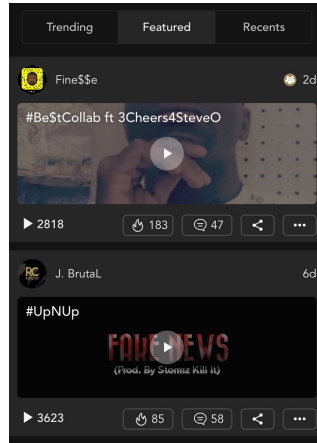


Figure 6. Discover tab on the social music platform mobile application for song discovery

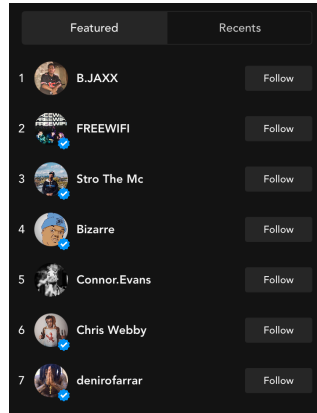


Figure 7. Discover tab on the social music platform mobile application for artist discovery

3.3.2 Experimental design

In order to test for the effectiveness of the availability of conflicting popularity information signals, we develop two popularity scores for the songs, one is based on all the users on the platform (popularity on platform) and the other is based on only the users a focal user is following (popularity among peers). Figure 8 and Figure 9 respectively depict the graphics used to convey the two information signals of interest to our study: popularity on platform and popularity among peers. Using colors, we visualize the popularity as being very low (in a white

color), low (in a yellow color), medium (in an orange color) or high (in a red color). Next, we randomly choose users and assign them to one of the three treatment groups.

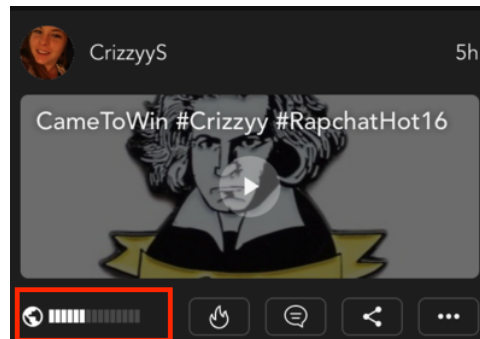


Figure 8. Graphical depiction of popularity on platform information signal

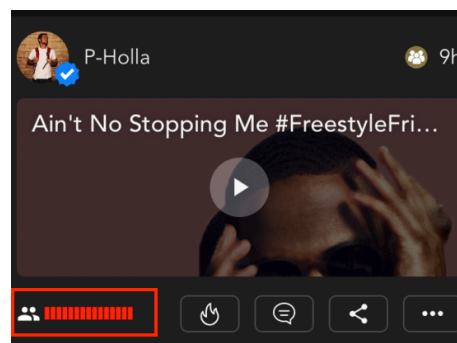


Figure 9. Graphical depiction of popularity among peers' information signal

For the first treatment group, we do not show any of the two popularity information signals (Figure 10). In the second experiment group, users are exposed to the default information signals of the app (the number of likes, comments and plays for a song) (Figure 11). In the next treatment group, users are exposed to both popularity on platform and popularity among peers information signals, and the two signals are randomly assigned such that the two signals are aligned with each other (Figure 12). In the last treatment group, users are exposed to both popularity on platform and popularity among peers' information signals, and the two signals are

randomly assigned such that the two signals are in conflict with each other (Figure 13). Table 14 summarizes the experiment groups and the treatment conditions.

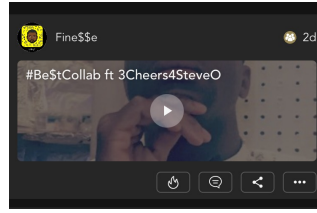


Figure 10. Design of the app for treatment group with no signal

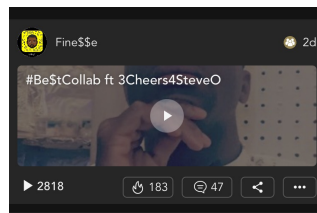


Figure 11. Design of the app for control group with default signal

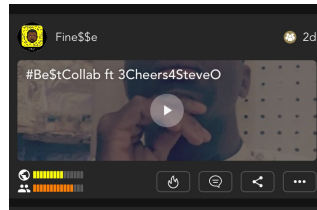


Figure 12. Design of the app for treatment group with conflicting signals

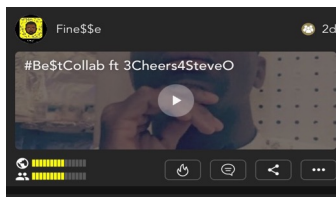


Figure 13. Design of the app for treatment group with aligned signals

Table 14. Experiment treatment conditions

Treatment	Experiment Group
No Signal	1
Platform Default Signal	2
Aligned Signals	3
Conflicting Signals	4

3.4 DATA COLLECTION AND ANALYSIS

3.4.1 Sample

Our sample includes 199 users, with 50 users in the no signal, default signal and conflicting signals groups, and 49 users in the aligned signals group. These users are randomly drawn from the pool of active users on the platform who have formed a social network of at least one person on the platform.

3.4.2 Variables

To measure dependent variables, we focus on users' search behavior and outcomes. We evaluate engagement and discovery by measuring the number of songs the user plays and the number of profiles of artists the user views in order to learn more about the artist. We also use the number of sessions started by the user as a covariate. This variable shows to be different among different experiment groups, and we control for it to account for variation in the amount of time the user spent in the experiment (See Figure 14).

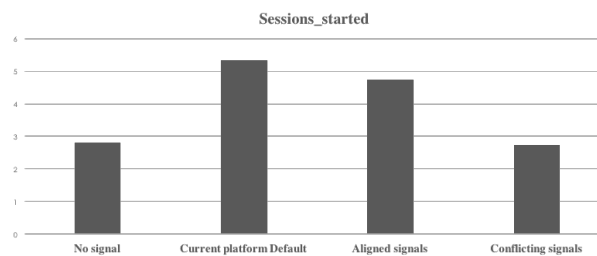


Figure 14. Number of sessions started in experiment groups

Table 15. Key variables and definitions

Variable	Definition
Songs_played	Number of songs the user played
Profiles_viewed	Number of artists' profiles viewed
Sessions_started	Number of sessions started on the app

3.4.3 Descriptive statistics

The descriptive statistics for the dependent variables and control variable is presented in Table 16. In Table 17 and Figure 15, the cell means for the experiment groups are presented. Table 18 presents the correlation between these variables.

Table 16. Descriptive statistics

	N	Mean	Std. Dev	Min	Max
Songs_played	199	13.47	47.02	0	586
Profiles_viewed	199	9.63	25.30	0	237
Sessions_started	199	3.91	6.42	0	36

Table 17. Cell means

treatment	Songs_played	Profiles_viewed	Sessions_started
No signal	6.94	5.2	2.82
Current Platform Default	7.96	6.04	5.34
Aligned signals	13.28	10.94	4.75
Conflicting signals	25.68	16.38	2.74

Table 18. Correlation matrix

	Songs_played	Profiles_viewed	Sessions_started
Songs_played	1		
Profiles_viewed	0.49	1	
Sessions_started	0.27	0.47	1

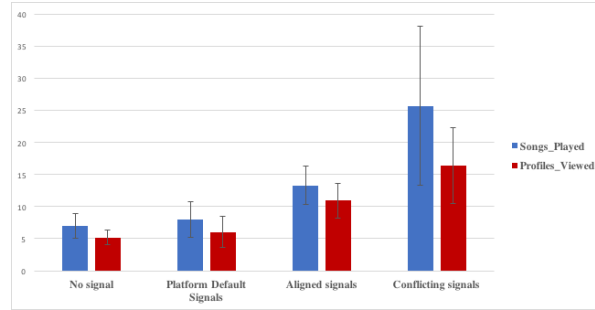


Figure 1. Cell means for dependent variables

3.4.4 Summary of results

To evaluate the hypothesis, we performed between-subject multivariate analysis of variance (MANOVA) on Songs_played and Profiles_viewed, as a function of the treatment groups (no signal, default signal, aligned signals and conflicting signals) and Sessions_started as a covariate. The summary of results is presented in Table 19. Pillai's trace test revealed a significant difference between treatments in influencing engagement ($p < 0.01$).

Table 19. Results of MANOVA

Effect	df	F	Sig.
Model	4	11.54	0.0000
Treatment	3	2.93	0.0083
Sessions_started	1	34.42	0.0000

- Pillai's trace test statistics are reported

We then proceeded to evaluate the hypothesis to examine whether the treatment with the conflicting signals results in significantly higher engagement and discovery than other treatments. Post estimation tests show that the treatment of conflicting signals results in greater engagement and discovery than when the users are exposed to no information signals (Pillai's Trace = 7.71, $p < 0.001$). Further, we compare the users exposed to conflicting signals with the

users who are exposed to the platform default signal and we find that the conflicting signals result in greater engagement and discovery than the default signal of the platform (Pillai's Trace = 6.98, $p < 0.001$). Lastly, to evaluate the effectiveness of the conflicting and aligned information signals, we compare the two treatment conditions, and the results suggest that the conflicting signals do a significantly better job in increasing users' engagement and discovery on the platform (Pillai's Trace = 2.87, $p < 0.05$). The results provide support for the proposed hypothesis of this study that the conflicting signals result in greater engagement and discovery by creating strong social information scent and influencing the users' search behavior in the environment (i.e. the music platform). Further, as a robustness check we evaluate the same model and perform the hypotheses tests without including the covariate in the model. The results remain consistent with the model which includes the covariate.

3.5 DISCUSSION AND CONCLUSION

The empirical question in this study is how digital content platforms can improve user engagement and discovery by exploiting elements of social design. Improving user engagement and discovery is critical for platforms as they are characterized by network effects, and higher volume of usage on one side (users) can encourage more activities on the other side (i.e. artists). Given the integration of platforms with social networks, relying on social influence can be a key strategy in invoking desired user behavior. By adopting the information foraging theory and social foraging model, in this study we evaluated how the use of popularity information signals, and the alignment or the conflict between signals, can increase user engagement and discovery.

The results of a randomized field experiment in the context of a music mobile platform app show that the use of popularity information signals can provide strong information scent,

guiding the users' search behavior and increasing user engagement and discovery. We find that when users are exposed to conflicting information signals, this leads to significantly greater engagement and discovery, measured as the number of songs played and the number of artists' profiles viewed.

This significance difference is observed when comparing exposure to conflicting signals with exposure to aligned signals, default signal of the platform and no signal. This finding is consistent with the model of information foraging behavior in the social foraging model. Accordingly, when information foragers (i.e. users) have access to diverse and non-redundant information hints from other users, they can maximize their finding of valuable information in their search. The implications of these findings for content platforms is that they can effectively rely on elements of social design in invoking desired user behavior. In doing so, platforms can capitalize on the presence of conflicting feedback and providing users with such signals to increase the diversity of information hints and reduce redundancy.

Additionally, given that content platforms are characterized by network effects, more engagement and discovery on the side of users can encourage and increase motivations for content providers and artists to contribute more to the platform. While in this study we focus on outcomes of interest on the users' side (i.e. engagement and discovery), future research can expand on the possible cross-side effects of users' exposure to conflicting signals on the content providers behavior. Other potential implications of users' exposure to conflicting information signals can be observed in the extent to which they explore and listen to familiar vs. novel content and artists and how this may influence the content providers' behavior differently.

For digital content platform businesses, improved loyalty of users can also be a critical success metric. As users listen to more songs, and also view more artists' profiles on the

platform, they can discover more content that they find valuable, and thereby increase their loyalty to the app. Given that the conflicting information signals lead to great engagement and discovery on digital content platforms, by extension they may also result in more user satisfaction and loyalty to the app. Future work can focus on how exposure to conflicting signals can influence users' satisfaction in their search behavior and loyalty to the platform. Additionally, further research using lab experiments can expand on how these conflicting information signals influence users' decision-making process that leads to more engagement and discovery of songs and artists. By adopting decision-making frameworks used in search contexts, we can further analyze the process through which the conflicting signals influence users' engagement and discovery on the platform.

Moving forward, one main limitation of our study that leaves room for further investigation into the effect of conflicting signals is that our analysis is performed at the user level. Alternatively, we can study the effect of conflicting information signals at the song level. From the perspective of a song-level analysis we can gain insight into how the conflicting signals influence the extent to which songs with different characteristics, as well as their artists, are played or viewed and receive attention from users.

Our study contributes to the literature on platform businesses, business transformation and social media. Platform businesses adopt a myriad of strategies to gain competitive advantage. One such strategy is to improve the design of the platform. In this study, we evaluate how adopting such a strategy and exploiting elements of social design in the design of the platform can help content platforms improve success metrics of user engagement and discovery. Further, while prior works in the areas of business transformation and social media have widely focused on social influence and its business value in the context of adoption or purchase of

products, we broaden the scope of measurement and value by evaluating the impact of social influence on engagement and discovery of users. Further, we expand on how social influence can be a driver of behavior by allowing variation in the alignment (or lack thereof) of the social information signals influencing users' behavior.

4.0 Diversification Strategy for Mobile App Developers: Understanding the Role of App Category Characteristics

4.1 INTRODUCTION

With the maturity of mobile app platforms and continuous growth of the app business, more and more app developers are focusing on strategically positioning their apps to increase visibility and improve profitability. The global mobile app revenue forecast for the year 2020 is \$189 billion, and has become a part of the world economy (Dogtiev 2017). To be able to appropriate this economic pie, strategic decision making on the side of app developers becomes crucial.

One such strategic decision is to decide for which app categories to develop to ensure growth and higher return on investment. For app developers, this is essentially a decision of which battleground to enter where their apps can have a higher chance of survival and success. However, such a decision can present a challenge as on one hand, the popularity of an app category may lure developers to it on the level of step into a category with a large demand (and hence a high adoption rate) , but on the other hand, which a popular category can be highly competitive and dominated by strong incumbents, which makes it difficult for new apps to stand out, gain visibility and earn revenue.

For app developers, making sensible business decisions requires an understanding of the economics underlying the market (Ifrach and Johari 2013) and not accounting for the potential effect of these app category's competitive characteristics on the developer's performance can have unwanted consequences. In one famous instance, Twitter recently switched its category from the more popular "Social Networking" category to the "News" category that is less crowded, largely due to the fact that the Social Networking category is strongly dominated by Facebook and other social networking giants (Perez 2016). Presumably, the purpose of the change was to give the

Twitter app more visibility and improve its adoption. Such a strategic move also indicates the importance of the category characteristic on the app development strategy and market performance.

The choice of app category is a common decision faced by both new developers and experienced developers who aim at improving their performance and gaining more revenue by diversifying their app offerings into different app categories. The choice of app category is extremely important for new developers as a good beginning lays a solid foundation for the subsequent growth and opens up the opportunity to expand into other categories. It is also crucial for established developers who want to leverage their current user base and diversify their product space. In the mobile app market, product diversification is a strategy widely adopted by app developers, and about 60 percent of developers have apps in more than one category (Lee and Raghu 2014).

The effects of the choice of app category and diversification on developers' performance depend on different factors such as app category characteristics and the competitive dynamics. Prior works in other industries (e.g. packaged software, video games) have looked at firms' product release and diversification attempts within an industry and into different product-markets. These studies show that the features of the product-market into which a firm enters influence the firm's performance. These features include competition within a product-market and popularity of the product-market based on the demand for it (Boudreau 2010; Cennamo and Santalo 2010; Markovich and Moenius 2009; Simonsohn 2010).

As mobile app platforms are characterized by the presence of network effects, these features of product-markets (i.e. app categories) are expected to play a strong role in influencing developers' decision making as well as their performance. In markets characterized by network

effects, a tension exists between two opposing forces: category concentration and category popularity. The category concentration increases as the competition within a category becomes more intense and more strong incumbents become dominant, making it harder for a developer to gain market share from the incumbents. This leads to a competition effect due to “congestion or glut of developers” (Boudreau 2012). The positive indirect network effect, on the other hand, is triggered as the category becomes more popular and enjoys a stronger demand (Venkatraman and Lee 2004). On mobile app platforms, there is very little understanding on how a developer should choose which categories to develop for, given the varying levels of competition and popularity across app categories.

As the developers decide which app category to develop for, the consequence of this decision depends on the category concentration and popularity. The category popularity determines the amount of demand available for all the apps in that category and a higher popularity means a bigger “pie” for everyone. The category concentration determines the extent to which other strong and powerful developers are competing to take a bigger share from the same “pie”. A higher concentration means that the market is dominated by very few strong competitors and it is more challenging to gain a share of the market than when the market is relatively equally shared among all competitors. Furthermore, as the influence of category popularity and concentration on the developers’ performance is more predictable, the trade-off between the two is ambiguous. It is unclear whether the stronger user base and the associated positive indirect network effects brought by a high popularity would make up for the intense competition and other negative effects of high category concentration; or that the negative effect of category concentration would outweigh the positive impact of category popularity and negatively influence the app’s performance. Given

these uncertainties, in this study, we focus on examining how category concentration and category popularity interact and influence the outcome of developers' app diversification strategy.

4.2 LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

4.2.1 Diversification strategy and the choice of product-market

Mobile app developers adopt different strategies to improve their performance on the platform and gain more revenue. One such strategy to improve developers' performance is the diversification of app offerings across categories. The diversification strategy is appealing for app developers because it enables them to benefit from heterogeneity of users' needs and taste (Bayus and Putsis Jr 1999; Brynjolfsson et al. 2011), exploit economies of scope (Cottrell and Nault 2004; Li and Greenwood 2004), avoid failure due to concentrated focus on one category (Cottrell and Nault 2004; Lee and Raghu 2014; Li et al. 2013), take advantage of the low barrier to entry to different app categories and utilize available development tools for apps in different categories (Lee and Raghu 2014).

Prior works have studied diversification strategy in different industrial contexts. Stern and Henderson (2004) study the effect of firms' within-industry diversification on the likelihood of firms' survival for US personal computer manufacturers. They find that in the constantly changing environment of personal computer industry where competitors release a high number of new products, releasing products outside the primary product line reduces the likelihood of failure (Stern and Henderson 2004). In the context of microcomputer software, Cotrell and Nault (2004) find that producing a new product into a new category or a new platform correlates with improved firm survival. However, if the firm does not appeal to new sets of customer needs, the new product cannibalizes the old ones and can reduce the probability of firm survival (Cottrell and Nault 2004).

In the packaged software market, Tanriverdi and Lee (2008) find that related diversification across platforms and across software product-markets complement each other and when the two strategies are implemented in combination, it improves sales growth and market share. However, only implementing one of the two strategies has a negative effect on the vendor's performance. They define product-market relatedness as the extent to which different products serve the needs of the same set of customers (Tanriverdi and Lee 2008). In contrast, the mobile app market is different from the traditional packaged software market in that online users are much more likely to purchase niche items (Brynjolfsson et al. 2011), providing incentives for developers to diversify and take advantage of the customers' heterogeneity and release in niche segments.

In the context of mobile app platforms, Lee and Raghu (2014) find that for app developers, expanding app offering across categories has greater practical significance. In their study, Lee and Raghu capture category popularity characteristics by counting the number of apps competing in a given app category, and examine its influence on the developer's diversification outcome. They find that apps released in categories with more competing apps have relatively lower odds of survival.

However, using the sheer number of apps in a category fails to account for the two opposing product-market characteristics identified by Venkatramen and Lee (2004). Venkatramen and Lee find that in the context of video game development, game developers strive to release their games on the most popular platforms while seeking to avoid highly competitive segments in which their games may not be differentiated. They suggest that there is a trade-off in releasing products in product-markets characterized with varying degrees of overlap density, which can make the game developers face intense competition by incumbents, and dominance, which triggers a positive indirect network effect and offers game developers a big potential for their new games.

Venkatramen and Lee suggest further investigation into this trade-off and its effects. In this study and in the context of mobile app development, we shed light on how the choice of app category given these two app category characteristics influences the diversification outcome in the context of mobile app platforms.

4.2.2 The trade-off due to the positive network effects and competition effects

In the platform markets that are characterized by network effects, network effects can play a role in influencing the strategy of market participants and their performance. In a *platform market*, an intermediary (platform) enables exchanges between two or more sides of the market (Eisenmann et al. 2006; Katz and Shapiro 1985; Rochet and Tirole 2003). Due to presence of positive *indirect network effects*, the net utility for participants on one side of the market increases as the participants on the other side of the market increases (Eisenmann et al. 2006; Rochet and Tirole 2006). On the mobile app platforms, the positive indirect effect for app developers is observed as they experience increasing return an increase in the number of users and the demand on the users' side. The *competition effect*, on the other hand, decreases the net utility for participants on one side of the market as there are more participants on the same side of the market (Eisenmann et al. 2006; Huotari 2017; Porch et al. 2015). Eisenman et al suggest that platform owners must be cautious about the strong effect of competition, as sellers on a platform prefer to see fewer direct rivals. On mobile app platforms, for instance, as there are more dominant app developers, the competition becomes more intense and app developers prefer to avoid facing such an intense competition with incumbents.

The interaction between positive indirect network effects and competition effects and their impact on platform dynamics have been studied in different contexts. Markovich and Moenius (2009) analytically model how the software firms select the hardware platform to release their

products and argue that the firms' incentive to invest and compete in quality upgrades is driven by two forces: making the hardware platform more attractive to draw more users to the platform (strengthening positive indirect network effect), and competing against other firms on the same platform (counteracting competition effect). As the quality difference between platforms increases, the incentive to strengthen the indirect network effect on the superior platform decreases. Similarly, when the quality difference between software products on one platform increases, the incentive for a software firm to compete by quality upgrades and hamper the competition effect decreases.

In the context of electronic markets, the clash of the positive indirect network effect and competition effect has been studied by examining the timing of listing products for sale by eBay sellers (Simonsohn 2010). The sellers try to sell their items in the evening time slot, as they neglect the competition due to an excess in number of sellers and are lured by the increased demand in the evening time. The findings suggest that selling products at the peak time exhibits lower selling rates and prices, which is because these sellers focus on the aggregated demand for their products, rather than the residual demand after accounting for the competition.

In the context of app development for handheld computer platforms, the tension between competition effect and positive indirect network effect and their influence on the innovation incentives of app developers has been studied (Boudreau 2012). While encouraging a large number of independent developers to develop for a computer platform has become a norm in platform businesses in an effort to increase innovation and variety of apps (due to an indirect network effect), this approach may in fact hinder innovation due to heightened competition and a congestion of developers (competition effect). The results show that competition effect

overwhelms a positive indirect network effect and an over-all crowding-out of innovation is observed.

The platform's sustained competitive advantage is also influenced by the tension between competition effects and positive indirect network effects. The results of an agent based simulation model shows that overcrowding of sellers on a platform causes a competition effect that can prevent a platform sustaining the competitive advantage it has gained due to large installed base and positive indirect network effect (Huotari 2017). In another study, Li et al. study the developer's entry decision into a mobile app category by accounting for the positive indirect network effect due to the number of existing developers (2014). This study finds that the size of the user base has a positive relationship with the developer's entry decision to a mobile app category, and that the number of existing developers has an inverted U-shaped relationship with the entry.

The trade-off between the positive indirect network effect and the competition effect can also influence the developers' performance when they release their app into an app category. In this study, we focus on how category popularity (due to a positive indirect network effect) and category concentration (due to a competition effect) can influence the developers' performance.

4.2.3 Hypotheses development

Prior works in the mobile app industry have explored the effects of these category characteristics on developer's diversification performance. Lee and Raghu find that developers' diversification into "less popular" as opposed to "more popular" categories improves developers' performance (2014). They rely on an industry report's classification of categories into less popular and more popular ones, based on the percentage of the apps in a category relative to the entire platform. Theoretically, however, the number of apps in a category can indicate its popularity, but may also

signal strong competition within the category. Therefore, it is important to distinguish these two category characteristics and examine how the underlying dynamics of network effects influence the diversification-performance relationship.

In order to identify and account for the competition effect on the developers' performance, we examine the concentration of competition in an app category. In a concentrated category, where strong incumbents dominate the market, it may be more difficult for a developer to stand out in the competition and gain a large market share. Therefore, due to a congestion of developers and competition effects, developing for these categories may hinder improvement to developer's performance by negatively affecting *the app's adoption*.

H1: *All else being equal, the degree of market concentration of the app category is negatively associated with the app's number of downloads.*

On the other hand, in order to account for the positive indirect network effect that the app developers can exploit, we consider the size of the demand for a given app category as *category popularity*. As there is a larger demand for an app category, the developers benefit from a larger user base. A larger user base increases the odds that an app developer can recover the fixed costs of developing apps. This can be a source of indirect network effects, creating positive feedback and increasing the potential return on investment. Therefore, developing for a category with more popularity will positively affect *the app's adoption*.

H2: *All else being equal, the degree of market popularity of the app category is positively associated with the app's number of downloads*

Based on these two characteristics, each category can be represented on a two-dimensional diagram that consist of the category concentration and category popularity axes. In this study, category concentration is measured as HHI (the Herfindahl-Hirschman index), a widely adopted measure of competition. A larger HHI value indicates higher market concentration and stronger

presence of incumbents. Category popularity is measured as sum of number of downloads for the top apps in the category. Based on the data collected for 12 categories, Figure 16 shows how these categories are dispersed along these two dimensions.

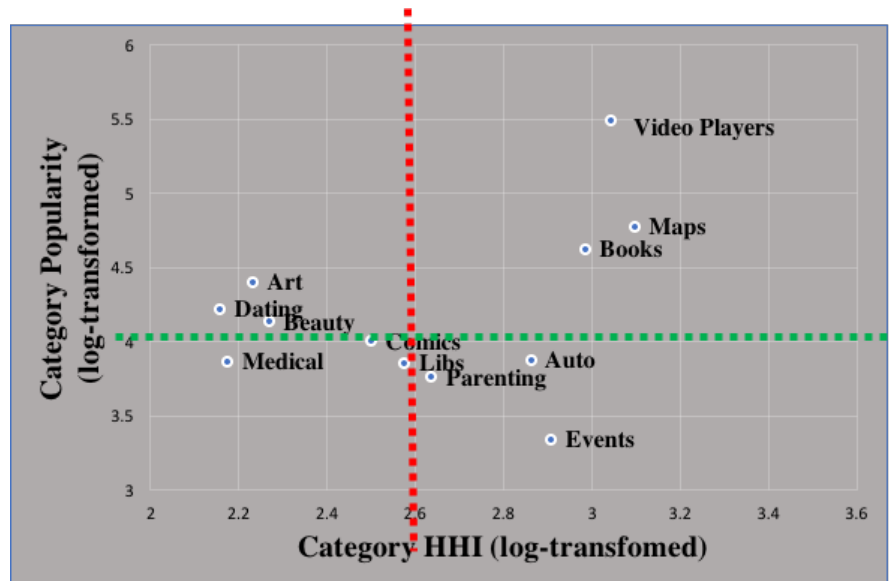


Figure 16. Dispersion of categories in the popularity-HHI dimensions
(*The dotted lines are drawn at the median value for log(popularity) and log(HHI))

Further, the effect of these two category characteristics may interact with each other. That is, the extent to which the developers can exploit the positive indirect network effects and the high popularity of a category positively influences the app's performance, may depend on the extent to which strong incumbents are present in the same category. Similarly, the extent to which the presence of a strong incumbent and high concentration of an app category negatively influences the app's performance depends on the size of the demand for the apps in that app category.

As the category popularity and category concentration influence the developers' performance, it is unclear whether the category popularity that is associated with a larger demand size would make up for the negative effect of category concentration and therefore improve an

app's performance; or that the negative effect of category concentration would overwhelm the positive impact of category popularity and negatively influence the app's performance. To test the relative effect of category concentration and category popularity, we hypothesize that:

***H3a:** All else being equal, the negative effect of market concentration of the app category is stronger than the positive effect of market popularity of the app category*

***H3b:** All else being equal, the positive effect of market popularity of the app category is stronger than the negative effect of market concentration of the app category*

4.3 DATA AND MEASURES

4.3.1 Sample

To test our hypotheses, we collected data for app developers, both new and those with previously released apps, and their mobile apps from the leading Android platform Google Play. On Google Play, both free and paid apps are categorized and ranked within each category. These Top Free apps and Top Paid ranking lists consist of the top 504 apps in their respective group based on their market performance. These lists allow us to measure the two category characteristics we are focusing on in this study. Google Play curates the Top Free and Top Paid apps for 12 app categories: Art & Design, Auto & Vehicles, Beauty, Books & References, Comics, Dating, Events, Libraries & Demo, Maps & Navigation, Medical, Parenting, Video Players & Editors. Thus, we focus on new apps released in these app categories to examine the effect of category characteristics on developers' diversification outcomes. Focusing on the new apps allows us to evaluate the effect of category characteristics, as we can collect data on these category characteristics at the time the new app is released.

In order to create a sample of new apps released in our list of categories, we collect weekly data from App Brain, a leading source of information about the Android ecosystem¹, which provides a comprehensive summary of the activity of Android mobile apps. The rich data provided by this website has also been utilized in previous studies (Liu et al. 2015). The weekly data collection of new apps span across an 8-week period in October and November of 2017, where we identify 1157 new apps released. For each of these apps, we also identify the developer and collect data on the developers' characteristics.

For the sample of our apps, we run a longitudinal weekly data collection on each app and its developer. We ran this data collection on AppBrain for a 10-week period from October 2017 to December 2017, creating a panel dataset with 10,026 observations for 1157 apps². For each app, we collected the weekly data on the following variables: estimated number of downloads, type of pricing (free vs. paid), app category, and the developer's name. For the developer, we collected the weekly data on the developer's number of apps and the average user review rating across all apps.

For each app, we also collected data on the list of top apps in the app's category in the week the app was released. For example, for a free app released in the Comics category in the second week of November, we collected the list of all the apps in the Top Free apps in the Comics category in the second week of November as curated by Google Play. If the app was paid, we collected the data from the Top Paid apps. For each app in the list, then, we collected the estimated number of downloads in the second week of November from AppBrain. Using the number of

¹ <https://www.appbrain.com>

² Note that this is not a balanced panel, since apps were released in different weeks and our data collection window for the new apps was ten weeks.

downloads for all the apps in the list, we then develop measures for category popularity and category concentration. This part of our data collection adds a cross-sectional observation for each app in our dataset, measuring the category popularity and category concentration in the week the app was released.

4.3.2 Variables and measurement

For the majority of our variables on the apps and the developers we use the data as they were collected from AppBrain. The dependent variable in this study, the number of downloads for the app released by a developer, is collected weekly from AppBrain. While on Google Play the exact number of downloads for apps is not available and instead a range of download counts are presented³, AppBrain uses its pool of data to estimate the number of downloads for each app. Use of the estimated downloads allow us to better evaluate the performance of the apps. Further, as the number of downloads is right-skewed, we use a logarithmic transformation to make it approximately symmetrically distributed.

For the independent variables of interest in this study, we develop measures of category popularity and category concentration. For this purpose, we rely on the data on list of top apps collected from Google Play and the estimated number of downloads for those apps collected from AppBrain.

To measure category popularity, we use the sum of number of downloads for all the apps in the top list of the apps in each category, as a proxy for the aggregated demand for the category. The concentration in an app category is measured by computing HHI, a measure of market

³ Google Play lists the number of downloads for the apps in one of 11 range categories: 10-50, 50-100, 100-500, 500-1,000, 1,000-5,000, 5,000-10,000, 10,000-50,000, 50,000-100,000, 100,000-500,000, 500,000-1,000,000, 1,000,000-5,000,000

concentration. A larger value of HHI indicates strong presence of incumbents and an intense competition, while a smaller value of HHI indicates less intense competition with many smaller firms. To compute HHI for a category, we calculate the market share of each app as a percentage of its number of downloads to the total number of downloads for all the apps in that category. We then use the following formula to compute HHI:

$$\text{CategoryHHI} = \sum (\text{market share for each app})^2$$

Table 20 provides definitions of the key variables and control variables used in our analyses, and Table 21 presents the descriptive statistics.

Table 20. Definition of Key Variables

Variable	Definition
$\text{Log}(\text{AppDownloads})_{i,t}$	The log of number of times app i has been downloaded (purchased) on week t .
CategoryHHI_i	Category concentration for the app i in the week the app is released
$\text{CategoryPopularity}_i$	Category popularity for the app i in the week the app is released
$\text{AppAge}_{i,t}$	The age of the app i (in weeks) on week t
$\text{DeveloperRating}_{i,t}$	The average of user review rating across all the apps developed by the developer of app i on week t
$\text{DeveloperNumApp}_{i,t}$	The number of apps developed by the developer of app i on week t

Table 21. Descriptive Statistics of Key Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
$\text{Log}(\text{AppDownloads})_{i,t}$	3.87	2.37	0	13.12
CategoryHHI_i (scaled in 100)	6.95	5.24	1.35	50.57
$\text{CategoryPopularity}_i$ (scaled in 1m)	23.33	44.01	.0001	172.56
$\text{AppAge}_{i,t}$	6.48	2.72	1	14
$\text{DeveloperRating}_{i,t}$	3.08	1.53	0	5

$DeveloperNumApps_{i,t}$	8.23	6.44	1	26
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4.4 ECONOMETRIC MODELS AND ESTIMATION RESULTS

4.4.1 Econometric models

To evaluate the proposed hypotheses, we construct two econometric models. In both models, the dependent variable is the log of number of downloads for a newly released app. The category HHI (scaled in 100) and category popularity (scaled in 1m) are the key independent variables. In our second model, we create an interaction term for the two category characteristics to evaluate the expected presence of an interaction effect between the two.

$$\begin{aligned} \text{Log(AppDownloads)}_{i,t} = & \alpha_0 + \alpha_1 \text{CategoryHHI}_i + \alpha_2 \text{CategoryPopularity}_i + \alpha_3 \text{AppAge}_{i,t} + \alpha_4 \\ & \text{DeveloperRating}_{i,t} + \alpha_5 \text{DeveloperNumApps}_{i,t} + \varepsilon_{i,t} \end{aligned}$$

Model 1

$$\begin{aligned} \text{Log(AppDownloads)}_{i,t} = & \beta_0 + \\ & \beta_1 \text{CategoryHHI}_i + \beta_2 \text{CategoryPopularity}_i + \beta_3 \text{CategoryHHI}_i * \text{CategoryPopularity}_i + \\ & \beta_4 \text{AppAge}_{i,t} + \beta_5 \text{DeveloperRating}_{i,t} + \beta_6 \text{DeveloperNumApps}_{i,t} + \varepsilon_{i,t} \end{aligned}$$

Model 2

Due to the panel nature of our dataset, we examine our model for specification error and violations of ordinary least squares (OLS) estimation assumptions so that we can make appropriate adjustments. We run tests for heteroscedasticity and autocorrelation. The result of the White's test rejects the null hypothesis that the variances for the errors are constant, suggesting the presence of heteroscedasticity. This is consistent with the visual inspection of the residuals which shows an increase in the residual variance as the fitted values increase. We further perform the Wooldridge test for autocorrelation in the panel data. The result shows that the null hypothesis of absence of

first-order autocorrelation (AR1) is rejected, suggesting presence of AR1 in our data set. This is expected given the longitudinal nature of our data. Given the presence of heteroscedasticity and AR1 autocorrelation in our models, we adopt the generalized least squares (GLS), estimator and use robust standard errors that account for both heteroscedasticity and autocorrelation.

4.4.2 Estimation results

To evaluate the effect of category characteristics on developers' diversification outcome, in model 1 we regress $\log(AppDownloads)$ on the *CategoryHHI* and *CategoryPopularity*, controlling for the app's age, and the developer's number of apps and average user review ratings across all apps. As shown in Table 22, the coefficients for the *CategoryHHI* (α_1) and *CategoryPopularity* (α_2) are both significant at the 1 percent level. The coefficient for *CategoryHHI* is negative, which suggests that as the category in which the developer releases an app is more concentrated, the app is less successful in acquiring more downloads, thus supporting H1.

Since the dependent variable of both models adopts a log-linear form, the result shows that a 100-unit increase in the *CategoryHHI* corresponds to approximately 4.2% expected decrease in the number of downloads for the app. The coefficient for *CategoryPopularity*, on the other hand, is positive. This positive coefficient supports H2 and shows that all else being equal, when the developer releases an app in a more popular category, the app will have a higher number of downloads than if it was released in a less popular category. The size of the coefficient suggests that a one-million-unit increase in category popularity corresponds to a 1.2% increase in the number of downloads for the app. Further, post-estimation test on the difference between α_1 and α_2 shows a significant difference between the two coefficients ($\chi^2(1) = 23.16, p < 0.01$), supporting

the hypothesis that the negative effect of the *CategoryHHI* is significantly stronger than the positive effect of *CategoryPopularity*, hence H3a is supported and H3b is rejected.

Table 22. Regression Results

Dependent Variable: log(AppDownloads)	<i>Model 1:</i> <i>GLS Estimation</i> (No interaction)	<i>Model 2^a:</i> <i>GLS Estimation</i> (With Interaction)
<i>CategoryHHI</i> (scaled in 100)	-0.042** (0.011)	-.129** (0.030)
<i>CategoryPopularity</i> (scaled in 1m)	0.012** (0.001)	.033** (0.006)
<i>CategoryHHI</i> * <i>CategoryPopularity</i>		-01.223** (0.345)
<i>AppAge</i> _{<i>i,t</i>}	0.211** (0.006)	0.211** (0.006)
<i>DeveloperRating</i> _{<i>i,t</i>}	0.331** (0.031)	0.331** (0.031)
<i>DeveloperNumApps</i> _{<i>i,t</i>}	0.043** (0.008)	0.041* (0.009)
Constant	1.186** (0.146)	1.687** (0.222)
Fit statistic (Wald χ^2)	1420.85**	1427.77**
^a In model 2, both <i>CategoryHHI</i> and <i>CategoryPopularity</i> are centered to create the interaction term. * $p < 0.05$; ** $p < 0.01$.		

In model 2, we include the interaction effect of the two category characteristics in the specification. To result shows a significant and negative interaction between *CategoryHHI* and *CategoryPopularity* in influencing the number of downloads for a new app. Since both *CategoryHHI* and *CategoryPopularity* are continuous variables, the inclusion of the interaction term of these two variables makes our model prone to multicollinearity. To avoid this threat, we center the original interacting variables before computing the interaction term. For the centered

variables, the mean is zero. This approach makes the interpretation of our results more straightforward and also greatly reduces the correlation between the interaction term and original variables.

The result of model 2 shows that the interaction between CategoryHHI and CategoryPopularity is significant and negative, and that consistent with model 1, there is a significant negative effect of CategoryHHI and a significant positive effect of CategoryPopularity on the number of downloads for an app released in a given category. For CategoryHHI, a 100-unit increase at the expected value of CategoryPopularity corresponds to a 12.9% decrease in the number of downloads, supporting H1. Supporting H2, a one-million-unit increase in CategoryPopularity at the expected value of CategoryHHI correlates with 3.3% increase in the number of downloads. The negative interaction of CategoryHHI and CategoryPopularity suggests that as a category becomes more popular, the negative effect of CategoryHHI becomes stronger. Similarly, as the category becomes more concentrated, the positive effect of CategoryPopularity diminishes. To evaluate H3a and H3b, we ran a *post-hoc* test of the coefficients for CategoryHHI and CategoryPopularity, and we found that the two coefficients are significantly different from each other ($\chi^2(1) = 20.81, p < 0.01$). This result supports H3a and rejects H3b, showing that the negative effect of CategoryHHI would outweigh the positive effect of CategoryPopularity.

4.5 DISCUSSION AND CONCLUSION

In this study, we conduct an empirical analysis to address the question of whether the characteristics of app categories, category concentration and category popularity, into which an app developer diversifies by releasing an app influences the number of downloads for the app and hence the performance of the developer. As we investigated the negative effect of category

concentration and the positive influence of category popularity on the app's performance, we also focused on which of the two forces will prevail.

The results show that when deciding on which app category to develop for, developers should account for category concentration and category popularity. We find support for H1, which predicts that releasing an app in a category with higher category concentration will have a negative impact on the app's downloads. On average, a 100-unit increase in HHI will reduce the app's number of downloads by about 12.9%. As discussed earlier, this negative impact is due to the fact that as strong incumbents dominate the competition in an app category, it becomes harder for new apps to stand out and attract users' attention. While some developers may find it intriguing to develop apps for categories where established apps are present to enjoy a possible spillover effect, our results suggest the opposite outcome due to the market power of strong incumbents.

Our results also provide support for H2, that category popularity has a positive influence on an app's performance. The interaction effect shows that the negative impact of category concentration is even stronger for the categories that have higher popularity. Because even though the high popularity means a bigger pie for everyone, the absolute loss due to the strong incumbents taking a bigger share of the same pie is larger in a highly concentrated category. Therefore, considering the positive effect of popularity, the developers should practice caution by considering the effect of category concentration. Although on average higher popularity increases the app's estimated downloads, this does not hold when the category is highly concentrated. For categories with low concentration, higher popularity has a positive impact on the app's performance. But when the category becomes concentrated and the HHI becomes larger than 710, an increase in popularity will in fact reduce the app's number of downloads. This finding is in line with the results supporting H3a, that the negative influence of category concentration would overwhelm the

positive impact of category popularity. This is also consistent with prior findings in other contexts on how crowdedness can create a glut of complementors, thereby suppressing innovation and reducing sales volume. In the mobile app context, we shed light on the two opposing characteristics that can influence the developers' diversification outcome differently, rather than relying on a single measure of the number of developers in an app category used in prior works. This is very illuminating given the dilemma the developers often face: either embrace the higher popularity or avoid the higher concentration.

The implication of our study can help developers diversifying their app offerings or releasing their first app with their choice of app category. By highlighting the importance of app category characteristics, our findings suggest that if developers are to choose between categories with *low concentration*, among those the categories with *higher popularity* will have the most positive influence on the app's performance. In such categories, the high popularity will enable the developers to exploit the positive indirect network effects and improve their performance by absorbing more demand from the pool of users. However, if developers are to choose between categories with *high concentration*, they are better off if they choose a category with *lower popularity*. This is because in categories with lower popularity, the dominance of the strong incumbents is more fragile, leaving room for new apps to compete against them. In categories with high concentration and high popularity, the strong incumbents are enjoying a strong and established dominance, making it even harder for developers to stand out.

Our study contributes to the literature on app developers' performance and strategic decision making, platform competition strategy and diversification strategy. We inform the literature on how diversification of app developers can be influenced by the characteristics of the app categories. Future work can tease out other prominent app category characteristics that can

play a role in developers' diversification outcomes. Further, this study contributes to the platform strategy literature by focusing on the competition among complementors. While there is a rich stream of research studying the competition between platforms, we contribute to this literature by evaluating the competitive strategies adopted by platform complementors (i.e. app developers) and how the positive indirect network effect and competition effect may oppose each other and differentially influence the complementors' performance. Further, as platforms compete with each other, the nature of competition within those platforms and among their complementors can be decisive of the platforms' evolution and success. Therefore, more research on the platforms' complementors competitive strategies can be instrumental in this line of research.

5.0 CONCLUSION

As the platform business model is becoming widely adopted, the world of business is witnessing a surge in the emergence of digital platform businesses. Digital platforms create value by enabling interaction and exchanges between platform participants on two (or more) sides of the market, often referred to as complementors and consumers. As digital platforms strive to gain the edge by adopting myriads of competitive strategies, one characteristic that can influence their efforts and strategic decision making is the presence of network effects.

Digital platforms are characterized by both direct and indirect network effects. With a positive direct network effect, joining more participants on one side increases the value for other participants on the same side. Direct network effects can also take a negative form, when the presence of more participants on one side decreases the value for the participants on the same side. With a positive indirect network effect, as more participants join one side of the platform, the participants on the other side can gain a higher value.

Network effects can be a significant source of influence on the competition in the world of platforms, where competition may take place between the platforms, between the complementors participating on the platforms, and in some cases between a platform and its complementors. Therefore, both platforms and the complementors need to acknowledge network effects as they focus on their strategic decision making, try to utilize positive network effects and practice caution in dealing with negative network effects. In the three essays of this dissertation, we have studied competitive strategies for digital platform business and have considered the role of network effects as a driving force.

The first essay, a study in the context of videogame consoles, we have focused on how multi-homing of videogame developers can weaken the indirect network effects and lead to a Winners-Take-Some (WTS) outcome competition outcome. This WTS outcome is typically not expected in the market for platforms, where a Winner-Takes-All (WTA) outcome often emerges due to the strength of indirect network effects. We analyzed three

hand-collected data sets on video games across classes of video game consoles and found a consistent, increasing pattern of multi-homing among the most popular video games. In the most recently concluded video game console competition that resulted in a WTS outcome, we find that 65% of the most popular games are multi-homing. We have argued why we observe this change in the multi-homing behavior of videogame developers and how it can mitigate indirect network effects and pave the way for a WTS outcome.

In the second essay, we turn our focus to a competitive strategy that content platform businesses can adopt to improve their performance, which is improving the design of the platform. As an emerging success metric for content platforms, we argued for the importance of user engagement and discovery. With improved user engagement one side content platforms can exploit a positive indirect network effect. We focused on using popularity information signals as a social design element to invoke the desired user behavior. In a field experiment in the context of a music mobile app platform we evaluated the effect of conflicting popularity information signals on user engagement. We found that for users who are exposed to *conflicting* information signals, their engagement and discovery is greater than for those users who are exposed to *aligned* popularity information signals.

In the third essay, and in the context of mobile app platforms, we analyzed hand-collected panel data of mobile app developers' diversification strategies and the performance of their newly released apps to evaluate the effect of mobile app categories on the apps' performance. We focused on the two mobile app category characteristics that are believed to be driven by network effects and competition effects: popularity of the mobile app category that can positively influence a mobile app's performance (due to positive indirect network effects), and the concentration mobile app category that can negatively influence a mobile app's performance (due to a negative competition effect). We found support for the hypotheses that both characteristics influence a mobile app's performance, and that the negative effect of category concentration overwhelms the positive effect of category popularity.

As proposed and tested in these essays, we observe a significant influence of network effects on competition in the world of platforms. As digital platform businesses are growing, both in number and in importance in the business world, the relevance of studying the challenges and dynamics of competition in the presence of network effects is on the rise. We contribute to our understating of how platforms and complementors can make better strategic decisions and account for network effects as they strive to gain competitive advantage.

Moving forward, we can build on the three essays in this dissertation to further our understanding of competition for platform owners and platform complementors. Given the emergence of WTS outcome in some platform markets, it will be worthwhile to study how similar outcome may arise in other contexts, such as the market for content platforms. This is because platform owners' strategies depend on whether they are to compete *for* the market to become the market leader, or compete *in* the market to be one of the players with enough market share to survive and succeed. The second chapter of this dissertation has focused on a platform market where the platform owners (i.e. video game console platforms) enable the exchange of physical goods (i.e. video games) and it involves a monetary transaction between the seller and buyer. On a content platform, on the other hand, platform owners enable the exchange of content and the focus is more on consumption, rather than purchase. In these platforms, the switching cost may be higher due to users customizing their consumption on the platforms (e.g. creating playlists of songs on a music platform). Varying levels of switching costs between content platforms depending on whether conversion tools between these customizations are available can differently influence the market outcome. For these content platforms, we can study what other factors such as switching costs can influence the market outcome and under what conditions an emergence of WTS can be expected.

Additionally, studying the competition dynamics within a given platform can also shed light on within-platform competitions. Understanding the dynamics of competition within and between app categories on a mobile app platform, for instance, can inform app developers on adopting appropriate competitive strategies. We can apply an ecological

theory to study the within and between category competitions. In ecology, individuals within a species compete with each other for resources (e.g. food). There is also a competition between species as there might be an overlap in the required resources for different species. Similarly, mobile apps compete with each other within an app category. For example, all the apps in the “Books” category compete with each other. Additionally, apps in a category and as a group compete with mobile apps from other app categories. For example, apps in the “Books” category compete with the apps in the “News” category. The later competition is due to the fact that users have limited physical storage on their phones and limited attention span for different kinds of apps. These competition dynamics within an app category and between the app categories can have implications for the strategies adopted by mobile app developers. For example, more compatibility between apps in the “Books” category can make the “Books” category more attractive to the users compared to the “News” category. But this compatibility might make it harder for the apps in the “Books” category to compete with each other. Therefore, by accounting for both within and between category competition, app developers can adopt more appropriate strategies.

Moreover, as platform owners and platform complementors compete for growth and competitive advantage, it is important to account for emerging success metrics and study how they can be improved. In the second essay of this dissertation we have studied how content platforms can improve user engagement as an emerging success metric by using social design features and including popularity information signals. While the user engagement may be an appropriate success metric in other platform contexts as well (e.g. video game console platforms, mobile app platforms), further work can study how this construct can be measured in such contexts. For video games, for instance, the micro-transactions that consists of with-in game purchases (e.g. purchasing in-game currencies, items, and random chances) can be used to measure user engagement. Further research can shed light on the choice of appropriate strategies for these platforms to improve such measures of user engagement.

To conclude, the three essays in this dissertation contribute to our understating of competition in the world of platforms by studying competitive strategies for both platform owners and platform developers, and the effectiveness of such strategies. The research questions addressed in this dissertation open up avenues of further inquiries to make broad contributions to both scientific literature and platform businesses.

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